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Frog in the Pan: Continuous Information and Momentum

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Abstract

We develop and test a *frog-in-the-pan* hypothesis that predicts investors are less attentive to information arriving continuously in small amounts than to information with the same cumulative stock price implications arriving in large amounts at discrete timepoints. Intuitively, we hypothesize that a series of gradual frequent changes attracts less attention than infrequent dramatic changes. Consistent with our frog-in-the-pan hypothesis, we find strong evidence that continuous information induces stronger and more persistent return continuation. Over a six-month holding period, momentum decreases monotonically from 8.86% for stocks with continuous information during their formation period to 2.91% for stocks with discrete information. Higher media coverage and higher analyst coverage are associated with more discrete and more continuous information, respectively.

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1 Introduction

Limited cognitive resources can prevent investors from immediately processing all available information. Sims (2003), Peng and Xiong (2006), as well as DellaVigna and Pollet (2007) provide theoretical foundations that allow limited attention to influence asset prices. Motivated by the notion that a series of gradual changes attracts less attention than a sudden dramatic change, we develop and test a frog-in-the-pan hypothesis. This hypothesis predicts that investors are less attentive to information arriving continuously in small amounts than to information with the same cumulative stock price implications arriving in large amounts at discrete timepoints.

According to the frog-in-the-pan anecdote, a frog will jump out of a pan containing boiling water since the dramatic temperature change induces an immediate reaction. In contrast, if the water in the pan is slowly raised to a boil, the frog will underreact and perish. In the psychology literature, Gino and Bazerman (2009) demonstrate that a series of small gradual changes induce less critical evaluation than large sudden changes. The cost of processing information, as in Merton (1987), also justifies the frog-in-the-pan hypothesis. For example, the cost of carefully reading an email is higher than the cost of reading its less informative subject header. Provided the amount of information in an email can be ascertained from its header, emails containing small amounts of information receive less attention even if they arrive frequently and are important in aggregate.

The existing literature on limited attention implicitly assumes the existence of an upper attention threshold that constrains the maximum amount of information on *all* firms that investors can process in a single period. For example, Hirshleifer, Lim, and Teoh (2009) find greater post-earnings announcement drift following days with a large number of earnings announcements. They conclude that investors are overwhelmed by the large amounts of information released on these days. In contrast, we posit the existence of a lower attention threshold for firm-specific information. Specifically, by failing to attract investor attention, the frog-in-the-pan hypothesis predicts an underreaction to information with important cumulative stock price implications that arrives continuously in small amounts.

To test our frog-in-the-pan hypothesis, we introduce a measure of information discreteness that describes the flow of information during a momentum strategy's formation-period. We then examine the impact of information discreteness on the holding-period returns of price momentum and earnings momentum strategies. With the exception of Hou, Peng, and Xiong (2008), the role of limited attention in explaining momentum has not been explored. Limited attention offers a middle ground between rational and behavioral explanations for momentum whose large respective literatures include Johnson (2002) and Daniel, Hirshleifer, and Subrahmanyam (1998). However, unlike the behavioral theories of Daniel, Hirshleifer, and Subrahmanyam (1998), Barberis, Shleifer, and Vishny (1998), and Hong and Stein (1999) that are designed to explain short-term return continuation as well as long-term return reversal, underreactions induced by limited attention will not lead to long-term return reversals.

Our first measure of information discreteness is derived from signed daily returns during the formation period.[1] Specifically, information discreteness identifies time series variation in the daily returns that culminate in equivalent formation-period returns. Intuitively, a high percentage of positive daily returns relative to negative daily returns implies that a high formation-period return is attributable to a large number of small positive returns instead of a few jumps. As the high formation-period return accumulated gradually over many days, the flow of information is continuous.[2] However, if the high formation-period return accumulated over a few days due to jumps, then the flow of information is discrete. Empirical evidence confirms that discrete information is associated with jumps in daily returns. Figure 1 provides a visual illustration of continuous versus discrete information.

We investigate whether information discreteness influences return continuation using double-sorted portfolios and Fama-MacBeth regressions. Consistent with our frog-in-the-pan hypothesis, continuous information induces stronger and more persistent return continuation than discrete information. Over a six-month holding period, price momentum increases from 2.91% in the discrete information portfolio to 8.86% in the continuous information portfolio. Furthermore, the momentum profit following continuous information persists for eight months while the momentum profit following discrete information is insignificant after two months. Moreover, the return predictability associated with continuous information does not reverse. This lack of long-term return reversal is consistent with investors underreacting to continuous information.

[1] Although daily stocks returns measure information with error because of market frictions and behavioral biases, this error is small relative to the amount of information underlying extreme formation-period returns.

[2] Frequent fluctuations in the aggregate stock market index are a source of continuous information that is relevant to individual stocks.

The return consistency dummy variable of Grinblatt and Moskowitz (2004) differs from information discreteness in several important dimensions.[3] Information discreteness is a continuous variable ranging from minus one to plus one that is defined using daily returns while return consistency is a dummy variable based on the sign of monthly returns. In contrast to our frog-in-the-pan hypothesis, one motivation for Grinblatt and Moskowitz (2004)'s investigation of return consistency is the disposition effect.[4] Tax loss selling in January is also investigated since return consistency cannot explain the continued poor performance of past losers. Indeed, return consistency only explains the return continuation of past winners since return reversals in January offset the return continuation of past winners with consistent returns. In contrast, following continuous information, we find no evidence of return reversals or weaker return continuation in January. Moreover, within the subsample of stocks with consistent returns (return consistency dummy variable equals one), portfolio double-sorts confirm that continuous information results in stronger momentum than discrete information. Overall, after controlling for return consistency, information discreteness continues to predict cross-sectional differences in momentum.

A large literature identifies firm characteristics that are related to the strength of momentum profitability. These characteristics include turnover (Lee and Swaminathan, 2000), size and analyst coverage (Hong, Lim, and Stein, 2000), book-to-market ratios (Daniel and Titman, 1999), return consistency (Moskowitz and Grinblatt, 2004), institutional ownership (Hou and Moskowitz, 2005), as well as idiosyncratic volatility (Zhang, 2006). To account for their correlation with information discreteness, we compute *residual* information discreteness by regressing information discreteness on these firm characteristics. Over a six-month holding period, price momentum increases from 3.19% to 8.57% as residual information discreteness in the formation period varies from discrete to continuous. Consequently, the return predictability of continuous information is distinct from firm characteristics in the existing momentum literature and is not attributable to the return consistency dummy variable in Moskowitz and Grinblatt (2004). Moreover, Fama-MacBeth regressions confirm that this predictability is not caused by a delayed reaction to information. Unlike Hou and Moskowitz (2005)'s price delay measure, information discreteness describes the flow of informa-

[3] Watkins (2003) defines a similar dummy variable to identify stocks whose prior monthly returns have the same sign as their cumulative formation-period returns.

[4] An alternative motivation for Grinblatt and Moskowitz (2004)'s investigation of return consistency is its impact on return volatility. The relative importance of idiosyncratic volatility versus information discreteness to return continuation is thoroughly addressed in our study.

tion. Indeed, while their price delay measure is a persistent firm characteristic that cannot explain momentum, the lack of autocorrelation in the information discreteness of individual firms is compatible with the need to frequently rebalance momentum portfolios. Barberis and Huang (2008) demonstrate that cumulative prospect theory allows the positive skewness of initial public offerings and distressed firms to result in negative excess returns. Besides controlling for return skewness in our Fama-MacBeth regressions, the removal of initial public offerings and distressed firms from our sample does not alter our results.[5] Consequently, skewness is not responsible for the return predictability of continuous information. Overall, after controlling for an array of firm characteristics including return consistency and skewness, Fama-MacBeth regressions indicate that information discreteness explains the profitability of both price momentum and earnings momentum strategies.

Zhang (2006) reports that momentum is stronger in stocks with higher idiosyncratic volatility during the formation period. Zhang interprets this finding as evidence that limits to arbitrage are responsible for return continuation. However, past winners and past losers have high idiosyncratic volatility during the formation period. More importantly, after accounting for the influence of formation-period returns on idiosyncratic volatility, we report that momentum is not stronger for stocks with higher idiosyncratic volatility. Consequently, limited attention rather than limits to arbitrage appears to explain cross-sectional differences in momentum profits.

The frog-in-the-pan hypothesis can apply to analysts as well as investors. We find that analyst forecast errors are larger following continuous information. This finding suggests that continuous information fails to attract analyst attention. Furthermore, a modified information discreteness measure defined by signed analyst forecast revisions also indicates that continuous information induces stronger momentum than discrete information.

[5]Although the Barberis and Huang (2008) model does not condition on the magnitude of prior returns, stocks with inconsistent returns may have positive skewness if their formation-period returns are high. In all our empirical tests, a $5 price filter is imposed. This filter eliminates the potential for low priced lottery stocks to influence our results.

To better understand the economic origins of information discreteness, we investigate the role of the financial media, management-issued press releases, and analyst coverage on information discreteness. This analysis connects information discreteness with the expanding literature that documents the media's influence on asset prices. This literature includes contributions by Tetlock (2007), Tetlock, Saar-Tsechansky, and Macskassy (2008), Fang and Peress (2009), and Tetlock (2010). Our findings indicate that higher media coverage, measured by the number of news articles appearing on the Dow Jones newswire, is associated with more discrete information. This finding is consistent with the financial media accumulating information before releasing their salient conclusions as well as the media's focus on major corporate events such as mergers and acquisitions. Indeed, media coverage and press releases capture an array of newsworthy corporate events. Moreover, consistent with the results in Peress (2009), greater media coverage appears to weaken return continuation by mitigating limited attention. Indeed, our study refines the channel through which media coverage produces discrete information and thereby weakens return continuation. In contrast, after controlling for media coverage, greater analyst coverage is associated with more continuous information. Consequently, lower analyst coverage does not imply stronger momentum provided a firm attracts sufficient media coverage.

The growing limited attention literature includes important contributions by Cohen and Frazzini (2008) on supplier-customer linkages as well as Da, Engelberg, and Gao (2009) on the popularity of information. This literature has recognized the need for information to attract investor attention with Barber and Odean (2008) reporting that small investors buy attention-grabbing stocks. However, the prior literature has not distinguished between continuous and discrete information, which is the central contribution of our paper.

The remainder of this paper is organized as follows. Section 2 describes the data and our measure of information discreteness. Section 3 then presents our results on the importance of information discreteness to momentum. The economic origin of information discreteness is examined in Section 4. Section 5 then concludes and offers suggestions for future research.

2 Data and Definitions

Return data is obtained from CRSP after adjusting for delistings. Shares splits are also accounted for using the split factor in CRSP. Firm-level accounting data is obtained from COMPUSTAT. Negative book values are eliminated from our sample period, which begins in 1976 and ends in 2007.[6] A total of 2,301,912 firm-month observations are available in our sample.

Information discreteness is determined by the sign of daily returns and ignores their magnitude by equally-weighting each observed return. The percentage of days during the formation period with positive and negative returns are denoted $\%pos$ and $\%neg$, respectively. Information discreteness, which is abbreviated ID, is defined as

$$\text{ID} \quad = \quad \text{sgn(PRET)} \cdot [\%neg - \%pos] \ , \tag{1}$$

where the cumulative return during the formation period (past twelve months after skipping the most recent month) is denoted PRET and its sign is denoted sgn(PRET), which is +1 when PRET > 0, -1 when PRET < 0, and 0 when PRET $= 0$. Specifically, PRET is defined as a firm's cumulative return over the past twelve months after skipping the most recent month. A large ID measure signifies discrete information while a small ID measure signifies continuous information.[7] For emphasis, information discreteness is interpreted after conditioning on the magnitude of formation-period returns. Intuitively, ID captures the "distribution" of daily signed returns, which ranges from a uniform distribution (continuous information) to a point mass (discrete information). Figure 1 provides a visual illustration of information discreteness. Observe that ID is robust to outliers whether PRET is near zero or large in absolute value.

For a winner stock with a high PRET, a time series of daily returns with a high percentage of positive returns ($\%pos > \%neg$) contains a large number of small positive returns and few jumps.[8] According to equation (1), the high percentage of positive returns yields a low value for ID. Indeed, if a series of daily returns are all positive, then ID equals its minimum value of -1 and corresponds to continuous information. In contrast, if the series of daily returns only contains one positive

[6] Our main results are nearly identical over a longer sample period starting in 1927. However, several firm characteristics are unavailable in the earlier subperiod.

[7] Morck, Yeung, and Yu (2000) estimate a similar measure to capture cross-sectional commonality in the returns within individual countries. In contrast, ID is estimated from a time series of returns for individual firms.

[8] With negative jumps, the percentage of positive daily returns must be even larger for a stock to be a past winner.

return, then ID approaches +1 and corresponds to discrete information. Conversely, for a loser stock whose PRET is low, a time series of daily returns with a high percentage of negative returns ($\%neg > \%pos$) contains a large number of small negative returns and few jumps. Consistent with information arriving continuously, this scenario also corresponds to a low value for ID. The noise in daily returns implies that ID measures the flow of information with error. Nonetheless, this measurement error is small relative to the extreme formation-period returns of winners and losers. Indeed, PRET provides a general measure of both the aggregate quantity and quality of information released during the formation period.

While ID does not differentiate between small and large daily returns, their magnitudes determine PRET. Indeed, by design, information discreteness is independent of the magnitude of daily returns since these magnitudes determine formation-period returns as well as return volatility. PRET also reflects a disproportionate number of either positive jumps or negative jumps within the formation period. However, despite increasing return volatility, jumps of the opposite sign are not relevant to our study of momentum provided PRET is near zero. The relationship between ID and jumps is examined using the following jump5 variable

$$\text{jump5} = [\text{5 largest positive and 5 largest negative daily returns}] \cdot \text{sgn(PRET)}\,, \tag{2}$$

and the following jump10 variable

$$\text{jump10} = [\text{10 largest positive and 10 largest negative daily returns}] \cdot \text{sgn(PRET)}\,. \tag{3}$$

The inclusion of sgn(PRET) enables the jump variables to be larger if negative jumps in the formation period are larger in absolute value than positive jumps. Thus, large values of jump5 and jump10 capture return skewness. However, jump5 and jump10 are near zero if the positive and negative jumps cancel each other since these variables are not intended to capture kurtosis.

To examine whether information discreteness is a firm characteristic, we estimate the price delay measure in Hou and Moskowitz (2005) that identifies neglected firms. These firms are identified by regressing firm-level weekly stock returns on contemporaneous market returns and lagged market returns over the prior four weeks. This time series regression is estimated for individual firms using weekly returns over the prior year, with its R-squared denoted R_L^2. The R-squared from a regression of firm-level weekly stock returns on contemporaneous market returns without lagged market returns is denoted R_C^2. The price delay measure is then defined as

$$D = 1 - \frac{R_C^2}{R_L^2} . \tag{4}$$

Intuitively, if prices rapidly incorporate market-level information, then lagged market returns are unimportant and R_C^2 is near R_L^2, with the D metric being closer to zero as a consequence. However, if prices slowly incorporate market-level information, then R_C^2 is far below R_L^2 and the D metric is closer to one. Thus, firms whose prices experience slower price reactions to market-level information have larger D metrics.

Hou and Moskowitz (2005) report that the D metric is a firm characteristic related to analyst coverage and institutional ownership that explains several return anomalies but not momentum. In contrast, information discreteness is not a persistent firm characteristic. Instead, information discreteness describes the flow of information to investors and varies over time for individual firms. Specifically, in December of every year, we compute ID over the prior calendar year for each firm in our sample. For the 2,500 firms with at least twenty annual ID measures, we regress each firm's ID measure on its prior calendar year's ID to compute first order autocorrelation coefficients. In unreported results, the cross-sectional average of these firm-level autocorrelation coefficients is 0.019. Therefore, unlike size, analyst coverage, or institutional ownership, information discreteness is not persistent but varies over time for individual firms.

The momentum literature identifies several firm characteristics that are related to the strength of momentum. Hou, Peng, and Xiong (2009) and Gervais, Kaniel, and Mingelgrin (2001) interpret low turnover as evidence of investor inattention while Lee and Swaminathan (2000) interpret high turnover as a sign of investor sentiment in their study of price momentum.[9] Furthermore, Zhang (2006) uses idiosyncratic volatility as a proxy for limits to arbitrage and reports stronger momentum profits in stocks with higher idiosyncratic volatility. We estimate idiosyncratic volatility (IVOL) using the residuals from a four-factor model involving daily returns, as in Fu (2009),

[9] Order flow imbalances over short horizons are not appropriate for measuring the flow of information. Liquidity shocks can induce large order flow imbalances but exert a small influence on returns. Conversely, important information can exert a large influence on returns but induce a small order flow imbalance if investors agree on its implications.

during the formation period. Zhang (2006) also finds that momentum is stronger in small firms and firms with less analyst coverage. Furthermore, Daniel and Titman (1999) document a negative relationship between the value premium and momentum. Hou and Moskowitz (2005) find that investor recognition characteristics such as institutional ownership and analyst coverage explain price delays while Hong, Lim, and Stein (2000) report that stocks with lower analyst coverage have stronger momentum.

To ensure that our findings regarding information discreteness are distinct from the existing momentum literature, we compute *residual* information discreteness.[10] Residual information discreteness is computed from a cross-sectional regression of ID on the absolute value of PRET along with firm characteristics that the existing literature has identified as being associated with cross-sectional differences in momentum profits

$$\begin{aligned} \mathrm{ID}_{i,t} \quad = \quad & \delta_{0,t} + \delta_{1,t}\,|\mathrm{PRET}|_{i,t} + \delta_{2,t}\,\mathrm{TURN}_{i,t} + \delta_{3,t}\,\mathrm{SIZE}_{i,t} + \delta_{4,t}\,\mathrm{BM}_{i,t} + \delta_{5,t}\,\mathrm{COVER}_{i,t} \\ & + \delta_{6,t}\,\mathrm{IVOL}_{i,t} + \delta_{7,t}\,\mathrm{IO}_{i,t} + \delta_{8,t}\,\mathrm{RC}_{i,t} + \epsilon^{ID}_{i,t}\,. \end{aligned} \tag{5}$$

Residual ID is defined as $\epsilon^{ID}_{i,t}$ for firm i in month t. Besides the absolute value of PRET, which captures the extreme formation-period returns underlying momentum, the other firm characteristics that define residual information discreteness include turnover (TURN), size (SIZE), book-to-market ratios (BM), analyst coverage (COVER), idiosyncratic volatility (IVOL), institutional ownership (IO), and a dummy variable for return consistency (RC). Analyst coverage is defined as one plus the log number of analysts issuing forecasts for a particular firm. Quarterly data on institutional ownership is obtained from the portfolio holdings reported in 13f filings with the SEC. These holdings are then normalized by the total number of shares outstanding to compute the percentage of shares held by institutions. Institutional ownership is then computed as one plus the log percentage of shares owned by institutions. The return consistency dummy variable equals one if a stock's monthly returns are positive (negative) for at least eight months of the twelve-month formation period and PRET is also positive (negative), as defined in Grinblatt and Moskowitz (2004).

Besides residual information discreteness, we compute residual IVOL, which is orthogonal to

[10] Unlike the slow diffusion of information in Hong, Lim, and Stein (2000), which pertains to the speed at which information is transmitted across investors, the frog-in-the-pan hypothesis pertains to the distribution of information across time. Indeed, small amounts of information can arrive continuously and be diffused rapidly across investors.

the absolute value of formation-period returns. This property is important since past winners and past losers have the highest absolute values of PRET. Residual IVOL is computed by the following cross-sectional regression

$$\text{IVOL}_{i,t} = \gamma_{0,t} + \gamma_{1,t} \, |\text{PRET}|_{i,t} + \epsilon_{i,t}^{IVOL} \,. \tag{6}$$

The $\epsilon_{i,t}^{IVOL}$ residual for firm i defines its residual idiosyncratic volatility in month t.

Table 1 summarizes the variables in our study and reports on their correlations. The summary statistics in Panel A indicate that ID has a mean near zero. According to Panel B, information discreteness is not highly correlated with idiosyncratic volatility. Moreover, while idiosyncratic volatility has a positive correlation with the absolute value of formation-period returns, information discreteness has a negative correlation. In unreported results, the time series average of the cross-sectional correlations between IVOL and |PRET| for past losers and past winners is more than double the correlation reported in Panel B. Thus, idiosyncratic volatility has a much higher correlation with the absolute value of formation-period returns for stocks selected by momentum strategies. The influence of extreme prior returns on idiosyncratic volatility is explored more thoroughly in the next section.

Panel A of Table 1 indicates that daily returns are positively skewed, while jump5 and jump10 are also positive on average. Furthermore, Panel B of Table 1 confirms that jumps are associated with discrete information. In particular, ID is positively correlated with skewness, kurtosis, jump5, and jump10. Information discreteness is also positively correlated with the price delay measure of Hou in Moskowitz (2005) in equation (4). Thus, continuous information does not correspond to the slow incorporation of information into stock prices. Moreover, the negative correlation between the return consistency dummy variable and ID indicates that continuous information coincides with a greater likelihood that monthly returns have the same sign as PRET. Therefore, our portfolio double-sorts and Fama-MacBeth regressions in the next section control for return consistency.

3 Information Discreteness and Momentum

To examine the importance of information discreteness to momentum, we form double-sorted portfolios sequentially that first condition on formation-period returns, then information discreteness. Specifically, after sorting stocks into quintiles according to their PRET, we then subdivide these quintiles into ID subportfolios. After imposing a $5 price filter, post-formation returns over the next six-months and three-years are then computed. These holding period returns are risk-adjusted according to the three-factor model of Fama and French (1993) that includes market, book-to-market, and size factors.

Panel A of Table 2 reports that momentum, the six-month return from buying winners and selling losers, decreases monotonically from 8.86% in the low ID quintile containing stocks with continuous information to 2.91% in the high ID quintile containing stocks with discrete information. This 5.95% difference is highly significant with a t-statistic of 5.13. Risk-adjusting the momentum returns increases the disparity between the six-month holding period returns to 6.89% (t-statistic of 7.01). In unreported results, the risk-adjusted returns are similar after including the liquidity factor of Pástor and Stambaugh (2003).

Figure 2 plots the momentum profits for the continuous and discrete information portfolios from one to ten months after portfolio formation. These momentum profits are not cumulative but represent "marginal" momentum profits within a particular month after portfolio formation. This figure indicates that significant momentum profits following continuous information persist for eight months. In particular, the momentum profit of 50bp (t-statistic of 2.27) in the eighth month after portfolio formation decreases to 21bp (t-statistic of 0.98) by the next month. In contrast, for stocks in the discrete information portfolio, the momentum profit of 32bp is insignificant by the third month after portfolio formation (t-statistic of 1.34). Therefore, momentum is stronger and more persistent following continuous information than discrete information.

The average ID, PRET, size, book-to-market ratio, analyst forecast dispersion, and IVOL corresponding to past winners and past losers in each of the ID quintiles are reported in Panel B. As in Jegadeesh, Kim, Krische, and Lee (2004), size is measured as the natural logarithm of a firm's market capitalization at the end of each quarter. These averages indicate that stocks with continuous information have similar characteristics as stocks with discrete information. Indeed, the variation in momentum profits identified by information discreteness does not appear to be associated with the size premium, value premium, or cross-sectional differences in earnings uncertainty. For example, continuous information is not limited to small stocks with high idiosyncratic volatility, nor is continuous information (low ID) concentrated in past losers. The firm characteristics in Panel B are studied in more detail below using Fama-MacBeth regressions.

Moreover, in unreported results, we confirm that the momentum profits in Table 2 are nearly identical if NASDAQ-listed firms are removed from the sample. Furthermore, the Fama-MacBeth coefficients in the next subsection involving information discreteness are also similar. Therefore, empirical support for the frog-in-the-pan hypothesis is not driven by stocks listed on NASDAQ.

Panel C of Table 2 reports the momentum profits from independent double-sorts derived from conditioning on PRET and information discreteness. The results in Panel C are similar to those in Panel A for sequential double-sorts, with momentum increasing from 1.63% to 8.33% over the six-month holding period as information during the formation period becomes more continuous. Thus, the impact of information discreteness on return continuation is not sensitive to whether the double-sorted portfolios are formed sequentially or independently.

According to Panel D, continuous information results in stronger momentum than discrete information within the subsample of stocks with consistent returns (return consistency dummy variable equals one). The subsample of stocks for which the return consistency dummy variable equals one comprises 17.24% of the firm-month observations in our original dataset. The results in Panel D indicate that the marginal return predictability of continuous information is significant after controlling for return consistency. Indeed, within the subsample of stocks with consistent returns, momentum increases monotonically across the information discreteness quintiles. The difference of 6.32% over the six-month holding period is significant (t-statistic of 5.18). Therefore, compared to the return consistency dummy variable, information discreteness is superior at identifying cross-sectional differences in momentum.

Moreover, Panel E reports that momentum is also monotonically increasing across the residual information discreteness portfolios. As detailed in equation (5), residual information discreteness accounts for return consistency as well as the absolute value of formation-period returns, turnover, size, book-to-market ratios, analyst coverage, idiosyncratic volatility, and institutional ownership. For the sequential double-sorts involving residual ID, momentum increases from 3.19% to 8.57%

across the residual information discreteness quintiles. This 5.38% difference is highly significant (t-statistic of 3.83) and confirms that information discreteness explains cross-sectional differences in momentum after controlling for existing variables in the momentum literature.

Overall, the momentum profits in Table 2 suggest that investors underreact to continuous information in a manner that is consistent with our frog-in-the-pan hypothesis. To clarify, the lack of short-term return continuation following discrete information does not contradict the concept of an upper threshold for investor attention. The maximum amount of information that investors can process in one day is determined by the aggregate amount of information regarding all firms released each day, as in Hirshleifer, Lim, and Teoh (2009)'s study. In contrast, our empirical tests focus on time series variation in the daily returns underlying twelve-month formation-period returns.[11]

An underreaction to information does not predict post-formation return reversals over the long term. Nagel (2001) argues that long-term return reversals are attributable to changing book-to-market characteristics. George and Hwang (2004) as well as Grinblatt and Moskowitz (2004) also cast doubt on the link between short-term return continuation and long-term return reversals. Grinblatt and Moskowitz (2004) attribute long-term reversals to tax-loss selling rather than investor overreaction. Tax loss selling in January provides one explanation for the inability of return consistency to explain the continued poor performance of past losers since the ability of return consistency to explain return continuation is limited to past winners in their study. The three-year holding-period returns in Table 2 are inconsistent with long-term return reversals for stocks in the low ID quintile with continuous information, despite their significant short-term return continuation. Indeed, stocks with continuous information in the formation period have higher long-term risk-adjusted returns than stocks with discrete information in the formation period. Moreover, in unreported results, we find no evidence of return reversals or weaker return continuation in January following continuous information.

Table 2 provides limited evidence that investors overreact to discrete information since discrete information during the formation period leads to negative (albeit insignificant) risk-adjusted returns in the three years after portfolio formation. Moreover, Figure 2 indicates that momentum profits following discrete information are negative within seven months of portfolio formation. Finally, a

[11] Industry and macroeconomic information as well as information regarding a firm and its peers are manifested in these daily returns.

6-1-6 momentum strategy whose formation period and holding period are both six months produces similar momentum profits as the 12-1-6 momentum strategy whose profits are reported in Table 2. In unreported results, profits from the 6-1-6 momentum strategy are monotonic across the information discreteness portfolios, providing a highly significant 10.34% unadjusted holding-period return in the low ID quintile.

3.1 Fama-MacBeth Regressions

We also estimate Fama-MacBeth regressions to determine whether continuous information is responsible for momentum after controlling for firm characteristics that the prior literature has shown to predict returns. The dependent variable in these regressions are individual stock returns over a six-month horizon. To examine price momentum, our cross-sectional regressions include formation-period returns (PRET). Similarly, to examine earnings momentum, standardized unexpected earnings (SUE) from the prior quarter are included in our regression analysis. An SUE is computed by comparing a firm's realized earnings in the most recent quarter with its realized earnings in the same quarter of the prior year, with this difference then normalized by the standard deviation of its earnings over the prior eight quarters.

Size and book-to-market ratios are also included in the cross-sectional regression since these characteristics are the basis for the Fama-French factors. Gervais, Kaniel, and Mingelgrin (2001) also document that turnover predicts returns and attribute this finding to the ability of high volume to overcome investor inattention. Therefore, we control for turnover in our Fama-MacBeth regressions. IVOL is also included in our cross-sectional regressions to ensure that the return predictability attributable to information discreteness is not a manifestation of idiosyncratic volatility's return predictability (Ang, Hodrick, Xing, and Zhang, 2006). In addition, Sadka (2006) reports that liquidity has a systematic component. Therefore, we include Amihud's measure (AMIHUD) in our cross-sectional regressions to control for illiquidity. For completeness, we include skewness (SKEW) and kurtosis (KURT) to account for the possibility that information discreteness is capturing these statistical properties of daily returns. The price delay metric (DELAY) of Hou and Moskowitz (2005) defined in equation (4) is also included to control for the speed at which investors incorporate information into stock prices.

Jegadeesh, Kim, Krische, and Lee (2004) identify several firm characteristics that predict returns. These characteristics include earnings-to-price ratios, total accruals to total assets, capital expenditures to total assets (CAPEX), previous sales growth, long-term analyst forecasts, and prior forecast revisions. Appendix A of Jegadeesh, Kim, Krische, and Lee (2004) defines each of these characteristics in detail. Total assets is defined using a firm's current assets.[12] CAPEX sums a firm's capital expenditures over the prior four quarters, on a rolling basis. Both total assets and CAPEX are quarterly variables normalized by a firm's total assets. Sales growth is a ratio whose numerator equals quarterly sales over the prior four quarters and whose denominator equals quarterly sales over a non-overlapping horizon consisting of the prior eight to four quarters. Prior forecast revisions are computed as annual consensus forecasts over the past six months normalized by price. These characteristics form a vector X of control variables whose individual coefficients are not reported for brevity.

Observe that several of the independent variables in equation (7) below are also independent variables in the computation of residual ID in equation (5). This commonality arises from the prior literature's use of firm characteristics such as size to predict returns and to explain cross-sectional differences in momentum profits.

We estimate several Fama-MacBeth (1973) regression specifications to evaluate the impact of information discreteness on return continuation. The first specification examines the influence of information discreteness on price momentum

$$\begin{aligned} r_{i,t+h} \;=\; & \beta_0 + \beta_1\,\mathrm{PRET}_{i,t} + \beta_2\,\mathrm{ID}_{i,t} + \beta_3\,(\mathrm{ID}\cdot\mathrm{PRET})_{i,t} + \beta_4\,\mathrm{SUE}_{i,t} \\ & + \beta_5\,\mathrm{SIZE}_{i,t} + \beta_6\,\mathrm{BM}_{i,t} + \beta_7\,\mathrm{TURN}_{i,t} + \beta_8\,\mathrm{IVOL}_{i,t} + \beta_9\,\mathrm{AMIHUD}_{i,t} \\ & + \beta_{10}\,\mathrm{SKEW}_{i,t} + \beta_{11}\,\mathrm{KURT}_{i,t} + \beta_{12}\,\mathrm{DELAY}_{i,t} + \alpha\,X_{i,t} + \epsilon_{i,t+h}\,. \end{aligned} \tag{7}$$

A separate specification replaces information discreteness with its residual counterpart in equation (5). The price momentum literature implies a positive β_1 coefficient. The β_2 coefficient captures the return predictability of information discreteness with a negative coefficient indicating that discrete information leads to poor future returns. More importantly, a negative β_3 coefficient for the interaction between formation-period returns and information discreteness, ID$\cdot$PRET, indicates

[12] Depreciation along with changes in cash, current liabilities, current long-term debt, and deferred taxes are then subtracted from current assets.

that continuous information results in stronger price momentum than discrete information. This interaction variable controls for the magnitude of formation-period returns when investigating the influence of information discreteness on price momentum. In particular, discrete information (high ID) corresponds with less return continuation if β_3 is negative.

Panel A and Panel B of Table 3 demonstrate the influence of information discreteness and residual information discreteness, respectively, on price momentum. In both panels, the β_1 coefficients for PRET are positive, which is consistent with price momentum, while the β_2 coefficients for information discreteness are insignificant. Although the ID variable itself does not exert a significant impact on momentum, the negative β_3 coefficients indicate that price momentum is stronger when information during the formation period is continuous. Recall that ID is an interaction variable whose interpretation is conditional on formation-period returns. In particular, discrete information (high ID) corresponds to weaker price momentum while continuous information (low ID) corresponds to stronger price momentum. This finding supports our frog-in-the-pan hypothesis. In addition, the negative β_3 coefficient involving residual ID in Panel B demonstrates that the return predictability of continuous information is not driven by its correlation with firm characteristics in the existing momentum literature.

In addition, the positive β_4 coefficients for SUE are consistent with the earnings momentum (post-earnings announcement drift) literature. Furthermore, the negative β_5 coefficients for size and positive β_6 coefficients for book-to-market are consistent with the higher returns of small stocks and value stocks relative to large stocks and growth stocks, respectively. The negative β_7 coefficient for turnover indicates that higher turnover in the formation period leads to lower subsequent returns. Amihud's liquidity measure, kurtosis, and the price delay measure have insignificant coefficients while the coefficient for skewness is negative. Using cumulative prospect theory, Barberis and Huang (2008) demonstrate that the positive skewness of initial public offerings and distressed firms can result in negative excess returns. Besides controlling for return skewness in our Fama-MacBeth regressions, unreported results demonstrate that removing initial public offerings (IPOs) and distressed firms from our sample does not alter our holding-period returns. IPOs are defined as firms whose initial appearance in CRSP occurs twelve months before portfolio formation, while firms are distressed if their KMV default scores are in the top decile.[13] The imposition of a

[13]A description of these default scores is available on http://www.moodyskmv.com/research/index.html.

$5 price filter also eliminates the potential for low priced lottery stocks to influence our results. Consequently, while discrete information coincides with positive skewness (according to Panel B of Table 1), skewness is not responsible for the return predictability of continuous information.[14]

Information discreteness also explains price momentum after controlling for the return predictability of idiosyncratic volatility. For emphasis, IVOL is computed during the formation period along with PRET and ID. Therefore, it is not directly comparable to the idiosyncratic volatility in Ang, Hodrick, Xing, and Zhang (2006) based on returns in the most recent month, which is omitted from the formation period. Bali, Scherbina, and Tang (2010) find short-term return reversal follows increases in idiosyncratic volatility, and link these increases with firm-level news. In contrast, the momentum profits following continuous information do not reverse. The lack of long-term return reversal provides further evidence that information discreteness is unrelated to idiosyncratic volatility.

In unreported results, computing IVOL using daily returns in the month prior to portfolio formation does not alter the return predictability of information discreteness. We focus our exposition on IVOL computed using weekly returns during the formation period for the sake of comparison with Zhang (2006). A detailed comparison of our results with Zhang is conducted in the next subsection. Furthermore, replacing the ID measure in equation (7) with |SKEW| does not result in a significant β_3 coefficient. Therefore, although skewness is correlated with discrete information according to Table 1, information discreteness is not captured by conventional moments of the return distribution. Finally, the addition of interaction variables involving PRET, such as TURN $\cdot$ PRET, and interaction variables involving ID, such as SIZE $\cdot$ ID, as well as triple interaction variables involving both PRET and ID, such as SIZE $\cdot$ PRET $\cdot$ ID, does not diminish the significance of the β_3 coefficients reported in Table 3. Therefore, it is unlikely that the ability of continuous information to identify cross-sectional variability in momentum profits is attributable to an omitted variable.[15]

To analyze the impact of information discreteness on earnings momentum, the following Fama-

[14] The negative coefficient for skewness indicates that stocks with positive skewness may have lower expected returns but function as a "lottery" by having a low probability of a high return. Bali, Cakici, and Whitelaw (2010) report that extremely large positive returns in the prior month, which are not included in formation-period returns, are associated with negative subsequent returns.

[15] The anchoring bias, which posits that investors are reluctant to update their strong prior beliefs, is also consistent with the return predictability of continuous information. For example, investors may require discrete information to overcome their strong prior beliefs. The inclusion of proxies for uncertainty such as IVOL as well as their interactions with ID and PRET control for the possibility that continuous information induces stronger return predictability when uncertainty is lower.

MacBeth regression is estimated

$$\begin{aligned} r_{i,t+h} &= \beta_0 + \beta_1 \, \mathrm{SUE}_{i,t} + \beta_2 \, \mathrm{ID}_{i,t} + \beta_3 \, (\mathrm{ID} \cdot \mathrm{SUE})_{i,t} + \beta_4 \, \mathrm{PRET}_{i,t} \\ &\quad + \beta_5 \, \mathrm{SIZE}_{i,t} + \beta_6 \, \mathrm{BM}_{i,t} + \beta_7 \, \mathrm{TURN}_{i,t} + \beta_8 \, \mathrm{IVOL}_{i,t} + \beta_9 \, \mathrm{AMIHUD}_{i,t} \\ &\quad + \beta_{10} \, \mathrm{SKEW}_{i,t} + \beta_{11} \, \mathrm{KURT}_{i,t} + \beta_{12} \, \mathrm{DELAY}_{i,t} + \alpha \, X_{i,t} + \epsilon_{i,t+h} \, . \end{aligned} \tag{8}$$

In this specification, the β_1 coefficient corresponds to the most recent SUE instead of formation-period returns, while the β_2 coefficients applies to information discreteness. Furthermore, the interaction variables underlying the β_3 coefficients involve the most recent earnings surprise, ID $\cdot$ SUE, instead of formation-period returns.

Panel C and Panel D of Table 3 demonstrate the influence of information discreteness and residual information discreteness, respectively, on earnings momentum. In both panels, the positive β_1 coefficients are consistent with earnings momentum. As with price momentum, the β_2 coefficients for information discreteness are insignificant. Instead, the negative β_3 coefficients indicate that earnings momentum is stronger for stocks with continuous information during the formation period. Thus, continuous information explains earnings momentum as well as price momentum. The positive β_4 coefficients for PRET account for price momentum while the remaining beta coefficients have similar interpretations as their counterparts in Panel A and Panel B. Overall, Table 2 and Table 3 provide strong empirical support for the frog-in-the-pan hypothesis.

3.2 Information Discreteness and Volatility

To address the possibility that information discreteness is higher (more discrete) when idiosyncratic volatility is higher, this subsection re-visits Zhang (2006)'s finding that momentum is stronger in stocks with higher idiosyncratic volatility. Besides the disposition effect, Grinblatt and Moskowitz (2004)'s study is also motivated by the possibility that return consistency impacts return volatility. The prior belief that continuous information corresponds to low idiosyncratic volatility suggests a contradiction between our finding that stronger momentum corresponds to continuous information and Zhang's finding that stronger momentum corresponds to high idiosyncratic volatility. Brav, Heaton, and Li (2009) conclude that as a proxy for limits to arbitrage, idiosyncratic volatility cannot explain the returns from past winners. Moreover, we emphasize that the relationship between idiosyncratic volatility and momentum reported in Zhang may be driven by a mechanical feature as the extreme returns that define winners and losers induce high idiosyncratic volatility.

We begin by sequentially forming double-sorted portfolios that first condition on IVOL, then PRET. Zhang (2006) also conditions on idiosyncratic volatility before conditioning on formation-period returns within the volatility portfolios. Post-formation holding period returns for the double-sorted portfolios over the subsequent six-months are then reported in Panel A of Table 4 along with long-term returns over the subsequent three years. Both unadjusted and risk-adjusted returns from the three-factor model are reported.

Consistent with Zhang (2006), Panel A of Table 4 presents evidence of stronger momentum in high IVOL stocks. From the low IVOL to high IVOL quintiles, momentum increases from 3.31% to 8.90% over a six-month horizon, a difference of 5.59%. However, as alluded to earlier, this finding may result from a mechanical relationship between high IVOL and extreme prior returns. To shed light on this issue, we reverse the order of the sequential double-sort by conditioning on PRET before IVOL.

The reverse double-sort examines the marginal return predictability of IVOL after controlling for formation-period returns. The results from this sequential double-sort in Panel B of Table 4 indicate a much weaker relationship between IVOL and momentum. Indeed, the 2.68% increase in momentum profits from the low IVOL quintile to the high IVOL quintile is much smaller than the 5.59% difference reported in Panel A. Consequently, the marginal return predictability of idiosyncratic volatility is weaker after controlling for the influence of formation-period returns.

Moreover, Panel C of Table 4 presents the returns from the same sequential double-sort underlying Panel B but with residual IVOL defined in equation (6) replacing IVOL. Residual IVOL is orthogonal to the absolute value of formation-period returns by construction. The results in Panel C provide evidence against the limits to arbitrage interpretation of high idiosyncratic volatility. Specifically, stocks with high residual IVOL produce a six-month momentum return of 6.87% while those low residual IVOL produce a momentum return of 6.62%. This difference of 0.25% is insignificant, which indicates that momentum is not stronger in stocks with higher idiosyncratic volatility after accounting for the influence of formation-period returns.

To summarize, Table 4 demonstrates that after controlling for the influence of formation-period returns on idiosyncratic volatility, higher idiosyncratic volatility is not associated with stronger momentum.

3.3 Analyst Forecasts and Information Discreteness

Besides investors, analysts may also underreact to continuous information. Indeed, continuous information can lead to larger earnings surprises defined relative to the consensus forecast of analysts if analysts are subject to the frog-in-the-pan phenomena. We obtain annual earnings per share forecasts from the Institutional Brokers Estimate System (IBES) Summary unadjusted file between 1985 and 2007. Unadjusted IBES forecasts are not adjusted by share splits after their issuance date.[16]

Using individual firm-level analyst forecasts, we construct consensus earnings per share forecasts for each firm. On any day an analyst forecast is observed, we calculate the consensus as the mean of all forecasts issued within the prior 30 days. If an analyst issues more than one forecast within the prior 30 days, we include their most current forecast in the consensus forecast calculation. Forecasts issued more than 365 days before the earnings report date are excluded, along with forecasts corresponding to realized earnings per share that exceed the share price. Following Livnat and Mendenhall (2006), analyst-based earnings surprises denoted SURP are defined as the difference between a firm's actual earnings per share and its IBES reported analyst consensus forecast. This difference is then normalized by the firm's share price on its earnings announcement date.

To test whether continuous information yields larger analyst forecast errors, we regress the absolute value of analyst forecast errors on information discreteness. Other variables that can affect the accuracy of consensus forecasts are included in this analysis. Analyst forecast dispersion captures the uncertainty surrounding a firm's earnings, and is computed as one plus the log standard deviation of analyst forecasts. Analysts may expend more effort on their earnings forecasts for stocks with high past returns and high turnover as well as growth stocks and large stocks if information on their future earnings is in greater demand by investors, including institutional investors (O'Brien and Bhushan, 1990), and can generate larger trading commissions. Therefore, we control for PRET, analyst forecast dispersion, analyst coverage, book-to-market ratios, size, turnover, and institutional ownership characteristics when examining the relationship between analyst forecast

[16] As detailed in Diether, Malloy, and Scherbina (2002), the earnings per share after a share split is often a small number that I/B/E/S rounds to the nearest cent. This rounding procedure can distort certain properties of dollar-denominated analyst forecasts such as their revisions and forecast errors.

errors and information discreteness.

To test the frog-in-the-pan hypothesis using analyst forecast errors, we estimate the following regression

$$\begin{aligned} |\mathrm{SURP}|_{i,t} &= \beta_0 + \beta_1\,\mathrm{ID}_{i,t} + \beta_2\,\mathrm{PRET}_{i,t} + \beta_3\,\mathrm{DISP}_{i,t} + \beta_4\,\mathrm{COVER}_{i,t} + \beta_5\,\mathrm{BM}_{i,t} \\ &\quad + \beta_6\,\mathrm{SIZE}_{i,t} + \beta_7\,\mathrm{TURN}_{i,t} + \beta_8\,\mathrm{IO}_{i,t} + \epsilon_{i,t}\,. \end{aligned} \tag{9}$$

A negative β_1 coefficient provides support for the frog-in-the-pan hypothesis. In particular, the negative β_1 coefficient implies that continuous information leads to larger analyst forecast errors.

Panel A of Table 5 contains the coefficient estimates from equation (9). Consistent with our frog-in-the-pan hypothesis, the β_1 coefficient is negative with a t-statistic of -4.66. This finding suggests that analysts are slower to incorporate continuous information into their forecasts than discrete information.

The negative β_2 coefficient indicates that earnings surprises are smaller for firms with higher formation-period returns. In addition, forecast uncertainty lowers analyst forecast errors as the β_3 coefficient is also negative. Analysts may exert additional effort on their forecasts when they deviate from the forecasts issued by their peers. The negative β_4 coefficient is consistent with greater analyst coverage reducing forecast errors. Consequently, more analysts lead to a more accurate consensus forecast even when their individual forecasts are disperse. Analysts also issue more accurate forecasts for large value firms with more institutional investors than small growth firms with less institutional investors. High turnover, which may be interpreted as disagreement between investors (not analysts), leads to larger forecast errors.

In addition, information discreteness in equation (1) can be constructed from analyst forecast revisions instead of returns where $\%up$ and $\%down$ are defined by upward and downward revisions, respectively, for the current fiscal year's forecasted earnings. The modification of ID using forecast revisions is denoted ID_f and equals

$$\mathrm{ID}_f = \mathrm{sgn}(\mathrm{CUMREV}) \cdot [\%downward - \%upward]\,. \tag{10}$$

The cumulative revision during the formation period is denoted CUMREV whose sign is +1 when

CUMREV > 0 (upward revision), -1 when CUMREV < 0 (downward revision), and 0 when CUMREV = 0. For every firm-fiscal year, we define CUMREV as the difference between the last consensus forecast before an annual earnings announcement and the first forecast. As with our original information discreteness measure in equation (1), ID_f in equation (10) is lower when information arrives continuously.

After estimating ID_f, we re-estimate equation (9) with ID defined by returns replaced with ID_f defined by analyst forecasts. The results in Panel B of Table 5 are similar to those reported in Panel A. Most importantly, the β_1 coefficient continues to be negative. The majority of the other coefficients have the same sign as their counterparts in Panel A although the significance of the coefficients for analyst forecast dispersion, analyst coverage, and institutional ownership declines.

We also repeat the cross-sectional regressions in equation (7) and equation (8) with ID_f replacing ID in the independent variables corresponding to the β_2 and β_3 coefficients. For price momentum, the Fama-MacBeth regression specification is

$$\begin{aligned} r_{i,t+h} \;&=\; \beta_0 + \beta_1\,\mathrm{PRET}_{i,t} + \beta_2\,\mathrm{ID}_{f\,i,t} + \beta_3\,\left(\mathrm{ID}_f\,\cdot\,\mathrm{PRET}\right)_{i,t} + \beta_4\,\mathrm{SUE}_{i,t} \\ &\quad +\beta_5\,\mathrm{SIZE}_{i,t} + \beta_6\,\mathrm{BM}_{i,t} + \beta_7\,\mathrm{TURN}_{i,t} + \beta_8\,\mathrm{IVOL}_{i,t} + \beta_9\,\mathrm{AMIHUD}_{i,t} \\ &\quad +\beta_{10}\,\mathrm{SKEW}_{i,t} + \beta_{11}\,\mathrm{KURT}_{i,t} + \beta_{12}\,\mathrm{DELAY}_{i,t} + \alpha\,X_{i,t} + \epsilon_{i,t+h}\,, \end{aligned} \tag{11}$$

and for earnings momentum the Fama-MacBeth regression specification is

$$\begin{aligned} r_{i,t+h} \;&=\; \beta_0 + \beta_1\,\mathrm{SUE}_{i,t} + \beta_2\,\mathrm{ID}_{f\,i,t} + \beta_3\,\left(\mathrm{ID}_f\,\cdot\,\mathrm{SUE}\right)_{i,t} + \beta_4\,\mathrm{PRET}_{i,t} \\ &\quad +\beta_5\,\mathrm{SIZE}_{i,t} + \beta_6\,\mathrm{BM}_{i,t} + \beta_7\,\mathrm{TURN}_{i,t} + \beta_8\,\mathrm{IVOL}_{i,t} + \beta_9\,\mathrm{AMIHUD}_{i,t} \\ &\quad +\beta_{10}\,\mathrm{SKEW}_{i,t} + \beta_{11}\,\mathrm{KURT}_{i,t} + \beta_{12}\,\mathrm{DELAY}_{i,t} + \alpha\,X_{i,t} + \epsilon_{i,t+h}\,. \end{aligned} \tag{12}$$

The results from these regressions are reported in Panel C and Panel D of Table 5, respectively. The β_3 coefficients for the interaction variables involving ID_f along with either PRET or SUE are both negative. Consequently, continuous information defined by analyst forecast revisions results in greater price momentum and earnings momentum than discrete information. Overall, Table 5 provides additional empirical support for the frog-in-the-pan hypothesis.

The coefficients for size and book-to-market characteristics have similar signs as their counterparts in Table 3. Although the beta coefficients for turnover and Amihud's measure are insignificant, the coefficients for skewness and kurtosis are negative and significant. Indeed, large positive jumps in the formation period precede poor returns over the next six-month horizon. Furthermore, as in Table 3, the beta coefficient for the price delay measure is insignificant.

4 Origin of Information Discreteness

Our next analysis explores the economics determinants of information discreteness. For example, we examine whether information arrives in large discrete amounts because the supply of information from management and the financial press is discrete.

Management press releases and coverage by the financial press are important internal and external sources of information, respectively. However, not all press releases receive media coverage. We examine press releases that do not receive media coverage within seven days (PR) and articles in the financial press (MEDIA) that do not occur within seven days of a press release to mitigate their confounding effects. The PR and MEDIA variables refer to the number of press releases and news articles in the prior year for an individual firm, respectively.

Corporate press releases are typically issued via newswire services. After firms distribute their press releases to newswire companies, press releases are disseminated to news distribution channels that include local newspapers, national newspapers, TV networks, and financial news services such as Bloomberg, Dow Jones/Factiva, and Thomson Reuters. News distribution channels may distribute these press releases depending on the newsworthiness of the press release and their news processing capacity. Our press release dataset contains all corporate press releases disseminated by PR Newswire from over 4,700 public companies which are traded on NASDAQ, NYSE, and AMEX from January 2000 to December 2007. Firms typically engage one newswire company at a given point in time. Neuhierl, Scherbina, and Schlusche (2010) report that nearly 60% of all publicly traded firms use PR Newswire. However, as our sample is not comprehensive, we restrict our analysis to firms that have at least one recorded press release in PR Newswire. In unreported results, firms using PR Newswire versus other alternatives do not differ in terms of firm characteristics such as firm size, growth, and industry affiliations. We match press releases to firm identifiers (CRSP permno) using the source identifier provided by PR Newswire, which includes the website URL of the issuing company as well as its name and address. We match these source identifiers to the company information in COMPUSTAT. To further improve the match quality, we use the soundex algorithm in SAS to match the firm names reported in the press releases with the firms names in COMPUSTAT. Our final sample contains over 220,000 press releases for 4,702 firms.

Our media data is obtained from Factiva, which contains media reports from several sources including newswires as well as local and national newspapers. From these sources, we focus on the most comprehensive financial news service, Dow Jones Newswire. Dow Jones Newswire obtains data from several sources including press releases, firm disclosures, and reports produced by financial journalists. As our sample begins in 2000, it does not suffer from the backfill bias reported in Tetlock (2010). To match news stories with financial databases, we use the ticker symbols, firm names, and name variants from the CRSP database as the search strings in Factiva using procedures outlined in Gurun and Butler (2010). Specifically, using a web crawler, we search name variants by singular and plural versions of the following abbreviations from the company names: ADR, CO, CORP, HLDG, INC, IND, LTD, and MFG. Our final sample includes over 420,000 firm-day media reports for 5,330 firms between 2000 and 2007.

Analysts represent another external information intermediary between firms and investors. Therefore, we include analyst coverage in our following analysis.[17] The prior literature (Bushee and Noe, 2000) reports that higher institutional ownership coincides with better disclosure by firms. Institutional investors often demand greater access to information while information may also be in greater demand for large firms that have more shareholders. Thus, our next analysis controls for institutional ownership as a proxy for corporate disclosure along with firm size. In addition, firm fixed effects are included in our analysis, which account for differences in information discreteness across industries.

To examine the determinants of information discreteness, we estimate the following Fama-

[17] Information intermediaries such as analysts and financial journalists can alter the discreteness of information by releasing salient information gradually or aggregating small amounts of information.

MacBeth regression

$$\begin{aligned}\mathrm{ID}_{i,t} &= \beta_0 + \beta_1\,\mathrm{PR}_{i,t} + \beta_2\,\mathrm{MEDIA}_{i,t} + \beta_3\,\mathrm{COVER}_{i,t} + \beta_4\,\mathrm{SIZE}_{i,t} \\ &\quad +\beta_5\,\mathrm{IO}_{i,t} + \beta_6\,|\mathrm{PRET}|_{i,t} + \epsilon_{i,t}\,. \end{aligned} \tag{13}$$

This regression is conducted separately for stocks with high and low formation-period returns since ID is an interaction variable whose interpretation requires us to condition on the magnitude of formation-period returns. In particular, equation (13) is estimated for stocks whose formation-period returns are above and below the cross-sectional median, while |PRET| is also included as an additional control variable.

The correlations between the independent variables in equation (13) are reported in Panel A of Table 6. PR and MEDIA are negatively correlated, both are positively correlated with analyst coverage and size. Thus, large firms have more analyst coverage, attract more media coverage, and issue more press releases than small firms. Panel B of Table 6 reports on the beta estimates for past winners. These coefficients are multiplied by 100 for ease of interpretation. The negative β_1 coefficient for PR indicates that management press releases (without media coverage) yield continuous information. The positive β_2 coefficient in Panel A implies that media coverage (unrelated to management press releases) produces discrete information. Intuitively, news articles appearing in the financial press are required to be sufficiently salient in order to be published. Indeed, media outlets follow a large number of firms, while management is only responsible for releasing information for their firm. Furthermore, major corporate events such as mergers and acquisitions that coincide with the discrete release of information are likely to attract media attention. Greater analyst coverage results in more continuous information since β_3 is negative. For past winners, larger firms and those with higher institutional ownership also have more continuous information as the β_4 and β_5 coefficients are both negative.

Panel C of Table 6 reports on the beta estimates from equation (13) for past losers. Once again, these coefficients are multiplied by 100 for ease of interpretation. In contrast to past winners, the β_1 coefficient for PR is insignificant. The β_2 coefficient for media remains positive but is less significant, implying that news articles on past losers have a marginal impact on information discreteness. Although press releases exert an insignificant impact on information discreteness for past losers, analyst coverage continues to lower information discreteness as the β_3 coefficient remains negative. Interestingly, the β_4 coefficient for size is positive for past losers. Thus, large firms that have done poorly in the formation period have more discrete information. In conjunction with discrete information resulting in weaker momentum, the more discrete information associated with large firms indicates that return continuation is stronger for small stocks that are past losers (Hong, Lim, and Stein, 2000).

In summary, articles in the financial press are associated with discrete information. Therefore, consistent with the results in Peress (2009), greater media coverage appears to weaken return continuation. Our study refines the channel through which greater media coverage produces more discrete information and consequently weaker return continuation. For past winners, management press releases produce continuous information although greater analyst coverage is associated with more continuous information for all firms. More importantly, lower analyst coverage does not necessarily imply stronger return continuation provided a firm attracts media coverage. Indeed, after controlling for media coverage, greater analyst coverage leads to more continuous information and stronger momentum.

5 Conclusions

We test a frog-in-the-pan hypothesis that predicts investors underreact to small amounts of information that arrive continuously. After controlling for the cumulative amount of information within the formation period, we find strong evidence that small amounts of information that arrive continuously predict returns and explain cross-sectional differences in momentum. Thus, consistent with our frog-in-the-pan hypothesis, investors appear to underreact to small amounts of information that arrive continuously, despite their important cumulative implications for stock prices.

Information discreteness is first defined using signed daily returns to distinguish between small amounts of information that arrive continuously versus information that arrives in large amounts at discrete points in time. Information discreteness identifies time series variation in the daily returns that comprise the formation-period returns underlying momentum strategies. The interpretation of information discreteness is conditional on a formation-period return. Indeed, only after conditioning on formation-period returns can one distinguish between the return implications of continuous versus discrete information.

Information discreteness is not influenced by extreme returns and differs from idiosyncratic volatility. Moreover, after accounting for the impact of extreme formation-period returns, higher idiosyncratic volatility is not associated with stronger momentum. Thus, information discreteness exerts a greater impact on momentum than idiosyncratic volatility. This finding suggests that limited attention is more important to explaining momentum than limits to arbitrage.

Analyst forecast errors are also larger following continuous information. Thus, analysts appear to underreact to continuous information. Furthermore, we define an alternative measure of information discreteness using signed analyst forecast revisions instead of signed daily returns. This alternative measure of information discreteness confirms that momentum is stronger following continuous information.

Greater media coverage by the financial press is associated with more discrete information, and weaker momentum as a consequence. In contrast, a larger number of management press releases is associated with more continuous information, but only for past winners. After controlling for media coverage and management press releases, greater analyst coverage corresponds to more continuous information for all firms. Overall, lower analyst coverage does not imply stronger return continuation provided a firm attracts sufficient media coverage.

References

Ang, A., R. Hodrick, Y. Xing, and X. Zhang, 2006, The cross-section of volatility and expected returns. Journal of Finance 61, 259-299.

Bali, T. G., N. Cakici, and R. F. Whitelaw, 2010, Maxing out: Stocks as lotteries and the cross-sectional of expected returns. Forthcoming in Journal of Financial Economics.

Bali, T. G., A. Scherbina, and Y. Tang, 2010, Unusual events and the cross-section of stock returns. Working Paper.

Barber, B., and T. Odean, 2008, All that glitters: The effect of attention and news on the buying behavior of individual and institutional investors. Review of Financial Studies 21, 785-818.

Barberis, N., and M. Huang, 2008, Stocks as lotteries: The implications of probability weighting for security prices. American Economic Review 98, 2066-2100.

Barberis, N., A. Shleifer, and R. Vishny, 1998, A model of investor sentiment. Journal of Financial Economics 49, 307-343.

Brav, A., J. B. Heaton, and S. Li, 2009, The limits of the limits of arbitrage. Review of Finance 14, 157-187.

Bushee, B., and C. Noe, 2000, Corporate disclosure practices, institutional investors, and stock return volatility. Journal of Accounting Research 38, 171-202.

Cohen, L., and A. Frazzini, 2008, Economic links and predictable returns. Journal of Finance 63, 1977-2011.

Da, Z., J. Engelberg, and P. Gao, 2009, In search of attention. Forthcoming in Journal of Finance.

Daniel, K., D. Hirshleifer, and A. Subrahmanyam, 1998, Investor psychology and security market under- and overreactions. Journal of Finance 53, 1839-1885.

Daniel, K., and S. Titman, 1999, Market efficiency in an irrational world. Financial Analyst Journal 55, 28-40.

DellaVigna, S., and J. Pollet, 2007, Demographics and industry returns. American Economic Review 97, 1667-1702.

Fama, E., and K. French, 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33, 3-56.

Fama, E., and J. MacBeth, 1973, Risk, return, and equilibrium: Empirical tests. Journal of Political Economy 81, 607-636.

Fang, L., and J. Peress, 2009, Media coverage and the cross-section of stock return. Forthcoming in Journal of Finance.

Fu, F., 2009, Idiosyncratic risk and the cross-section of expected stock returns. Journal of Financial Economics 91, 24-37.

George, T., and C. Y. Hwang, 2004, The 52-week high and momentum investing. Journal of Finance 59, 2145-2176.

Gervais, S., R. Kaniel, and D. Mingelgrin, 2001, The high-volume return premium. Journal of Finance 61, 877-919.

Gino, F., and M. Bazerman, 2009, When misconduct goes unnoticed: The acceptability of gradual erosion in others' unethical behavior. Journal of Experimental Social Psychology 45, 708-719.

Grinblatt, M., and T. Moskowitz, 2004, Predicting stock price movements from past returns: The role of consistency and tax-loss selling. Journal of Financial Economics 71, 541-579.

Gurun, U. G., and A. Butler, 2010, Don't believe the hype: Local media slant, local advertising, and firm value. Working Paper.

Hirshleifer, D., S. Lim, and S. Teoh, 2009, Driven to distraction: Extraneous events and underreaction to earnings news. Journal of Finance 64, 2289-2325.

Hong, H., T. Lim, and J. Stein, 2000, Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies. Journal of Finance 55, 265-295.

Hong, H., and J. Stein, 1999, A unified theory of underreaction, momentum trading, and overreaction in asset markets. Journal of Finance 54, 2143-2184.

Hou, K., L. Peng, and W. Xiong, 2009, A tale of two anomalies: The implication of investor attention for price and earnings momentum. Working paper.

Hou, K., and T. Moskowitz, 2005, Market frictions, price delay, and the cross-section of expected returns. Review of Financial Studies 18, 981-1020.

Jegadeesh, N., J. Kim, S. Krische, and C. Lee, 2004, Analyzing the analysts: When do recommendations add value? Journal of Finance 59, 1083-1124.

Johnson, T. C., 2002, Rational momentum effects. Journal of Finance 57, 585-608.

Lee, C., and B. Swaminathan, 2000, Price momentum and trading volume. Journal of Finance 55, 2017-2069.

Livnat J., and R. Mendenhall, 2006, Comparing the post-earnings announcement drift for surprises calculated from analyst and time series forecasts. Journal of Accounting Research 44, 177-205.

Merton, R., 1987, A simple model of capital market equilibrium with incomplete information. Journal of Finance 42, 483-510.

Morck, R., B. Yeung, and W. Yu, 2000, The information content of stock markets: Why do emerging markets have synchronous stock price movements. Journal of Financial Economics 58, 215-260.

Nagel, S., 2001, Is It Overreaction? The Performance of Value and Momentum Strategies at Long Horizons. Working Paper.

Neuhierl, A., Scherbina, A., and B. Schlusche, 2010, Market reaction to corporate news and the influence of the financial crisis. Working Paper.

O'Brien, P., and R. Bhushan, 1990, Analyst following and institutional ownership. Journal of Accounting Research 28 (Supplement), 55-76.

Pástor, L., and R. F. Stambaugh, 2003, Liquidity risk and stock returns. Journal of Political Economy 111, 642-685.

Peng, L., and W. Xiong, 2006, Limited attention, overconfidence and category learning. Journal of Financial Economics 80, 563-602.

Peress, J., 2009, Media coverage and investors' attention to earnings announcements. Working Paper.

Sadka, R., 2006, Momentum and post-earnings announcement drift anomalies: The role of liquidity risk. Journal of Financial Economics 80, 309-349.

Sims, C., 2003, Implications of rational inattention. Journal of Monetary Economics 50, 665-690.

Tetlock, P., 2007, Giving content to investor sentiment: The role of media in the stock market. Journal of Finance 62, 1139-1168.

Tetlock, P., 2010, Does public financial news resolve asymmetric information? Forthcoming in Review of Financial Studies.

Tetlock, P., M. Saar-Tsechansky, and S. Macskassy, 2008, More than words: Quantifying language to measure firms' fundamentals. Journal of Finance 63, 1437-1467.

Watkins, B., 2003, Riding the wave of sentiment: An analysis of return consistency as a predictor of future returns. Journal of Behavioral Finance 4, 191-200.

Zhang, F., 2006, Information uncertainty and stock returns. Journal of Finance 61, 105-137.

Table 1: Summary Statistics

Panel A of this table reports summary statistics for information discreteness (ID) defined as sgn(PRET) $\cdot$ [$\%neg - \%pos$] in equation (1) where $\%pos$ and $\%neg$ denote the respective percentage of positive and negative daily returns during the formation period. Summary statistics are also reported for formation-period returns (PRET), idiosyncratic volatility (IVOL), two jump variables, skewness, kurtosis, the price delay measure (DELAY) of Hou and Moskowitz (2005), and the return consistency dummy variable (RC) defined in Grinblatt and Moskowitz (2004). Summary statistics include the mean and standard deviation (Std. Dev.) along with the 25th, 50th, and 75th percentiles. Information discreteness captures the distribution of daily returns across the formation period. Continuous information arrives frequently in small amounts while discrete information arrives infrequently in large amounts. PRET corresponds to a firm's formation-period return in the prior twelve months after skipping the most recent month, while IVOL is estimated according to Fu (2009) within the same period. The jump5 variable is defined in equation (2) using the sum of the five largest daily positive returns and the sum of the five largest daily negative returns. Similarly, jump10 is defined in equation (3) using the largest ten daily returns. The price delay measure is defined in equation (4) while the return consistency dummy variable equals one if a stock's monthly returns are positive (negative) for at least eight months of the twelve-month formation period and PRET is also positive (negative). Residual IVOL is computed in equation (6) as the residual from the following cross-sectional regression, $\mathrm{IVOL}_{i,t} = \gamma_{0,t} + \gamma_{1,t}\, |\mathrm{PRET}|_{i,t} + \epsilon_{i,t}^{IVOL}$. Residual ID is computed in equation (5) as the $\epsilon_{i,t}^{ID}$ residual from the following cross-sectional regression, $\mathrm{ID}_{i,t} = \delta_{0,t} + \delta_{1,t}\, |\mathrm{PRET}|_{i,t} + \delta_{2,t}\, \mathrm{TURN}_{i,t} + \delta_{3,t}\, \mathrm{SIZE}_{i,t} + \delta_{4,t}\, \mathrm{BM}_{i,t} + \delta_{5,t}\, \mathrm{COVER}_{i,t} + \delta_{6,t}\, \mathrm{IVOL}_{i,t} + \delta_{7,t}\, \mathrm{IO}_{i,t} + \delta_{8,t}\, \mathrm{RC}_{i,t} + \epsilon_{i,t}^{ID}$, using firm characteristics that include turnover (TURN), size (SIZE), book-to-market ratios (BM), analyst coverage (COVER), idiosyncratic volatility (IVOL), institutional ownership (IO), and the dummy variable for return consistency. Panel B contains the correlations between the variables in Panel A.

Panel A: Summary statistics

	Mean	Percentiles 25th	50th	75th	Std. Dev.
ID	-0.034	-0.065	-0.031	0.000	0.053
residual ID	0.000	-0.031	0.002	0.031	0.051
PRET	0.177	-0.189	0.078	0.367	0.904
|PRET|	0.430	0.125	0.279	0.528	0.815
IVOL	0.517	0.053	0.139	0.385	4.321
residual IVOL	0.000	-0.432	-0.189	-0.037	4.304
skewness	0.212	-0.166	0.186	0.611	1.392
kurtosis	7.337	1.468	3.109	7.184	14.021
jump5	0.058	-0.022	0.036	0.120	0.189
jump10	0.087	-0.019	0.059	0.172	0.238
DELAY	0.562	0.293	0.568	0.849	0.303
RC	0.180	0.000	0.000	0.000	0.384

Panel B: Correlations

	ID	residual ID	PRET	|PRET|	IVOL	residual IVOL	skewness	kurtosis	jump5	jump10	DELAY	RC
ID	1											
residual ID	0.156	1										
PRET	0.068	0.020	1									
|PRET|	-0.101	-0.002	0.710	1								
IVOL	-0.012	-0.002	-0.084	0.102	1							
residual IVOL	-0.003	-0.002	-0.149	0.000	0.992	1						
skewness	0.088	0.013	0.248	0.110	-0.007	-0.017	1					
kurtosis	0.023	0.002	-0.022	0.051	0.016	0.010	0.010	1				
jump5	0.229	0.040	0.209	0.209	0.017	0.007	-0.034	0.266	1			
jump10	0.260	0.047	0.260	0.253	0.020	0.008	0.000	0.231	0.962	1		
DELAY	0.051	0.005	-0.014	0.027	0.053	0.043	0.086	0.098	0.059	0.069	1	
RC	-0.301	-0.000	0.092	0.167	0.017	0.007	0.013	-0.034	-0.018	-0.001	-0.002	1

Table 2: Double-Sorted Portfolios

This table reports post-formation returns from sequentially double-sorted portfolios involving formation-period returns and information discreteness defined in equation (1) as sgn(PRET) $\cdot$ $[\%neg - \%pos]$ where $\%pos$ and $\%neg$ denote the respective percentage of positive and negative daily returns during the formation period. PRET corresponds to a firm's formation-period return in the prior twelve months after skipping the most recent month. Information discreteness captures the distribution of daily returns across this formation period. Continuous information arrives frequently in small amounts while discrete information arrives infrequently in large amounts. Both unadjusted returns and risk-adjusted returns relative to the three-factor model of Fama and French (1993) are presented over six-month and three-year post-formation horizons. The results in Panel A are from sequential double-sorts involving formation-period return (PRET) quintiles, then information discreteness (ID) quintiles. Post-formation momentum returns, defined as the return from buying winners and selling losers, for each of the five information discreteness quintiles are presented. Panel B records the average ID, PRET, size measured as the log of a firm's market capitalization, book-to-market ratio (BM), log of analyst forecast dispersion, and idiosyncratic volatility (IVOL) for past winners and past losers across the information discreteness quintiles. Panel C reports on the returns from independent double-sorts (rather than the sequential double-sorts in Panel A) that condition on PRET and information discreteness. In Panel D, after implementing the sequential double-sorting procedure underlying Panel A, only the holding-period returns of stocks whose return consistency dummy variable equals one are reported. The holding-period returns in Panel E are from a sequential double-sort with information discreteness replaced by residual information discreteness. Residual ID is obtained from equation (5) as the $\epsilon_{i,t}^{ID}$ residual from the following cross-sectional regression, $\mathrm{ID}_{i,t} = \delta_{0,t} + \delta_{1,t}\,|\mathrm{PRET}|_{i,t} + \delta_{2,t}\,\mathrm{TURN}_{i,t} + \delta_{3,t}\,\mathrm{SIZE}_{i,t} + \delta_{4,t}\,\mathrm{BM}_{i,t} + \delta_{5,t}\,\mathrm{COVER}_{i,t} + \delta_{6,t}\,\mathrm{IVOL}_{i,t} + \delta_{7,t}\,\mathrm{IO}_{i,t} + \delta_{8,t}\,\mathrm{RC}_{i,t} + \epsilon_{i,t}^{ID}$, involving firm characteristics in the existing momentum literature. These firm characteristics include turnover (TURN), size, book-to-market ratios, analyst coverage (COVER), idiosyncratic volatility, institutional ownership (IO), and a dummy variable for return consistency (RC). As defined in Grinblatt and Moskowitz (2004), the return consistency dummy variable equals one if a stock's monthly returns are positive (negative) for at least eight months of the twelve-month formation period and PRET is also positive (negative). All t-statistics are Newey-West adjusted with six lags and reported in italics.

Panel A: Sequential double-sorts involving formation-period returns and information discreteness

ID	Winner 1	2	3	4	Loser 5	Average ID	unadjusted six-month return	*t*-stat	three-factor six-month alpha	*t*-stat	unadjusted three-year return	*t*-stat	three-factor three-year alpha	*t*-stat
discrete	8.38	7.83	7.42	6.83	5.47	0.03	2.91	*2.10*	4.84	*5.19*	-4.63	*-0.90*	-4.37	*-0.88*
2	10.06	9.46	8.26	7.40	5.39	-0.01	4.67	*3.89*	6.46	*7.21*	1.64	*0.36*	1.95	*0.44*
3	11.52	9.80	8.63	7.44	4.80	-0.03	6.72	*5.75*	8.88	*9.30*	5.89	*1.26*	6.25	*1.37*
4	11.31	9.49	8.46	7.24	3.89	-0.06	7.42	*6.27*	9.70	*9.60*	3.52	*0.71*	5.28	*1.20*
continuous	11.08	9.12	8.38	7.15	2.22	-0.10	8.86	*6.82*	11.72	*9.70*	8.07	*1.47*	11.77	*2.49*
continuous - discrete						-0.13	5.95	*5.13*	6.89	*7.01*	12.69	*2.45*	16.20	*3.55*

Panel B: Firm characteristics of sequentially double-sorted portfolios

ID	ID Winner	ID Loser	PRET Winner	PRET Loser	Size Winner	Size Loser	BM Winner	BM Loser	Dispersion Winner	Dispersion Loser	IVOL Winner	IVOL Loser
discrete	0.03	0.01	97.82	-20.76	11.34	10.71	0.52	0.71	0.04	0.08	0.54	0.29
2	-0.02	-0.03	101.51	-23.53	11.26	10.61	0.56	0.72	0.06	0.08	0.38	0.33
3	-0.04	-0.05	108.08	-25.92	11.37	10.79	0.55	0.73	0.05	0.10	0.32	0.33
4	-0.07	-0.08	113.3	-28.98	11.64	10.97	0.52	0.72	0.06	0.08	0.26	0.30
continuous	-0.11	-0.12	129.85	-35.15	12.16	11.13	0.49	0.70	0.05	0.07	0.18	0.30

Panel C: Independent double-sorts involving formation-period returns and information discreteness

ID	Winner 1	2	3	4	Loser 5	Average ID	unadjusted six-month return	unadjusted six-month *t*-stat	three-factor six-month alpha	three-factor six-month *t*-stat	unadjusted three-year return	unadjusted three-year *t*-stat	three-factor three-year alpha	three-factor three-year *t*-stat
discrete	7.95	7.79	7.58	7.16	6.32	0.04	1.63	*1.03*	3.48	*3.93*	-0.40	*-0.07*	-1.59	*-0.29*
2	9.72	9.19	8.48	7.32	5.56	-0.01	4.16	*3.37*	6.11	*5.48*	-1.93	*-0.41*	-0.98	*-0.22*
3	10.58	9.45	8.38	7.55	4.95	-0.03	5.63	*4.87*	7.54	*8.82*	-0.23	*-0.05*	1.72	*0.38*
4	11.16	9.77	8.47	6.97	4.59	-0.06	6.57	*5.72*	8.96	*10.08*	4.45	*0.94*	5.63	*1.23*
continuous	11.13	9.01	8.13	6.86	2.80	-0.10	8.33	*6.66*	10.94	*9.73*	6.77	*1.25*	8.98	*1.88*
continuous - discrete						-0.14	6.70	*4.65*	7.46	*5.42*	7.16	*1.31*	10.57	*2.08*

Panel D: Sequential double-sorts involving formation-period returns and information discreteness for stocks with consistent returns

ID	Winner 1	2	3	4	Loser 5	Average ID	unadjusted six-month return	unadjusted six-month *t*-stat	three-factor six-month alpha	three-factor six-month *t*-stat	unadjusted three-year return	unadjusted three-year *t*-stat	three-factor three-year alpha	three-factor three-year *t*-stat
discrete	10.78	9.89	10.36	8.40	6.19	0.00	4.59	*2.80*	6.69	*4.88*	-5.18	*-0.76*	-3.87	*-0.55*
2	12.31	11.32	10.23	8.72	5.36	-0.04	6.95	*4.23*	8.66	*5.39*	8.97	*1.22*	10.84	*1.34*
3	12.00	10.98	9.66	8.20	4.61	-0.07	7.39	*4.57*	9.48	*6.35*	7.19	*1.02*	9.00	*1.23*
4	11.97	10.85	9.97	7.79	4.23	-0.09	7.74	*4.55*	9.42	*6.59*	5.04	*0.68*	7.98	*1.07*
continuous	12.56	10.67	8.83	8.13	1.65	-0.14	10.91	*6.14*	13.79	*8.25*	5.07	*0.74*	8.16	*1.28*
continuous - discrete						-0.13	6.32	*5.18*	7.10	*6.08*	10.25	*1.73*	12.03	*2.03*

Panel E: Sequential double-sorts involving formation-period returns and residual information discreteness

residual ID	Winner 1	2	3	4	Loser 5	Average residual ID	unadjusted six-month return	unadjusted six-month *t*-stat	three-factor six-month alpha	three-factor six-month *t*-stat	unadjusted three-year return	unadjusted three-year *t*-stat	three-factor three-year alpha	three-factor three-year *t*-stat
discrete	8.50	7.89	7.46	6.82	5.31	0.06	3.19	*2.13*	5.07	*4.98*	-6.65	*-1.28*	-6.52	*-1.26*
2	10.45	9.43	8.24	7.41	5.31	0.02	5.14	*4.21*	6.58	*7.10*	2.37	*0.47*	2.47	*0.49*
3	11.12	9.77	8.62	7.46	4.79	0.00	6.33	*5.31*	8.36	*8.54*	4.62	*1.01*	5.61	*1.31*
4	11.31	9.49	8.45	7.26	3.98	-0.02	7.33	*6.01*	9.82	*8.87*	5.39	*1.10*	7.17	*1.64*
continuous	10.98	9.12	8.38	7.11	2.41	-0.07	8.57	*6.62*	11.53	*9.40*	8.80	*1.62*	12.18	*2.63*
continuous - discrete						-0.13	5.38	*3.83*	6.46	*5.70*	15.45	*2.85*	18.70	*3.87*

Table 3: Return Predictability of Continuous Information

The table reports on the coefficient estimates from equation (7) and equation (8) that examine the influence of continuous information on price momentum and earnings momentum, respectively. PRET corresponds to a firm's formation-period return in the prior twelve months after skipping the most recent month. Information discreteness captures the distribution of daily returns across the formation period. Continuous information arrives frequently in small amounts while discrete information arrives infrequently in large amounts. Price momentum and earnings momentum are studied by including formation-period returns (PRET) and earnings surprises (SUE) as independent variables, respectively. The information discreteness measure denoted ID is defined in equation (1) as $\text{sgn(PRET)} \cdot [\%neg - \%pos]$ where $\%pos$ and $\%neg$ denote the respective percentage of positive and negative daily returns during the formation period. Residual ID is obtained from equation (5) as the $\epsilon_{i,t}^{ID}$ residual from the following cross-sectional regression, $\text{ID}_{i,t} = \delta_{0,t} + \delta_{1,t}\,|\text{PRET}|_{i,t} + \delta_{2,t}\,\text{TURN}_{i,t} + \delta_{3,t}\,\text{SIZE}_{i,t} + \delta_{4,t}\,\text{BM}_{i,t} + \delta_{5,t}\,\text{COVER}_{i,t} + \delta_{6,t}\,\text{IVOL}_{i,t} + \delta_{7,t}\,\text{IO}_{i,t} + \delta_{8,t}\,\text{RC}_{i,t} + \epsilon_{i,t}^{ID}$, using firm characteristics that include turnover (TURN), size (SIZE), book-to-market ratios (BM), analyst coverage (COVER), idiosyncratic volatility (IVOL), institutional ownership (IO), and a dummy variable for return consistency (RC). The return consistency dummy variable equals one if a stock's monthly returns are positive (negative) for at least eight months of the formation period and is motivated by the definition of return consistency in Grinblatt and Moskowitz (2004). In Panel A, the interaction variable involving information discreteness and formation-period returns captures the influence of information discreteness on price momentum in the following Fama-MacBeth regression $r_{i,t+h} = \beta_0 + \beta_1\,\text{PRET}_{i,t} + \beta_2\,\text{ID}_{i,t} + \beta_3\,(\text{ID} \cdot \text{PRET})_{i,t} + \beta_4\,\text{SUE}_{i,t} + \beta_5\,\text{SIZE}_{i,t} + \beta_6\,\text{BM}_{i,t} + \beta_7\,\text{TURN}_{i,t} + \beta_8\,\text{IVOL}_{i,t} + \beta_9\,\text{AMIHUD}_{i,t} + \beta_{10}\,\text{SKEW}_{i,t} + \beta_{11}\,\text{KURT}_{i,t} + \beta_{12}\,\text{DELAY}_{i,t} + \alpha\,X_{i,t} + \epsilon_{i,t+h}$. Besides formation-period returns (PRET), earnings surprises (SUE), and information discreteness (ID), this regression specification includes control variables for size, book-to-market ratios, turnover, idiosyncratic volatility, Amihud's liquidity measure (AMIHUD), skewness (SKEW), kurtosis (KURT), and the price delay (DELAY) measure in equation (4). The X vector contains a multitude of control variables: earnings-to-price ratios, total assets, capital expenditures to total assets, sales growth, institutional ownership, and analyst coverage. Panel B reports on a similar regression specification with information discreteness replaced by residual information discreteness. In Panel C, the influence of information discreteness on earnings momentum is captured by interaction variable defined as the product of earnings surprises and information discreteness in $r_{i,t+h} = \beta_0 + \beta_1\,\text{SUE}_{i,t} + \beta_2\,\text{ID}_{i,t} + \beta_3\,(\text{ID} \cdot \text{SUE})_{i,t} + \beta_4\,\text{PRET}_{i,t} + \beta_5\,\text{SIZE}_{i,t} + \beta_6\,\text{BM}_{i,t} + \beta_7\,\text{TURN}_{i,t} + \beta_8\,\text{IVOL}_{i,t} + \beta_9\,\text{AMIHUD}_{i,t} + \beta_{10}\,\text{SKEW}_{i,t} + \beta_{11}\,\text{KURT}_{i,t} + \beta_{12}\text{DELAY}_{i,t} + \alpha\,X_{i,t} + \epsilon_{i,t+h}$. The results in Panel D are from replacing information discreteness with residual information discreteness. The t-statistics are Newey-West adjusted with six lags and reported in italics.

Panel A: Cross-sectional regressions of price momentum on information discreteness

	intercept	PRET	ID	ID·PRET	SUE	SIZE	BM	TURN	IVOL	AMIHUD	SKEW	KURT	DELAY	X	adj. R^2
coefficient	0.1203	0.0202	-0.0092	-0.1509	0.0034	-0.0033	0.0225	-0.0279	0.1287	-0.0004	-0.0029	-0.0001	0.0006	Yes	0.149
t-stat	*6.47*	*4.96*	*-0.54*	*-4.45*	*4.83*	*-2.57*	*7.25*	*-3.99*	*6.22*	*-0.05*	*-3.01*	*-0.09*	*0.13*		

Panel B: Cross-sectional regressions of price momentum on residual information discreteness

	intercept	PRET	residual ID	residual ID · PRET	SUE	SIZE	BM	TURN	IVOL	AMIHUD	SKEW	KURT	DELAY	X	adj. R^2
coefficient	0.1198	0.0258	0.0298	-0.2041	0.0033	-0.0033	0.0227	-0.0281	0.1296	-0.0002	-0.0027	0.0000	0.0013	Yes	0.149
t-stat	*6.47*	*6.50*	*1.93*	*-5.91*	*4.63*	*-2.56*	*7.30*	*-3.98*	*6.31*	*-0.03*	*-2.98*	*-0.04*	*0.27*		

Panel C: Cross-sectional regressions of earnings momentum on information discreteness

	intercept	SUE	ID	ID·SUE	PRET	SIZE	BM	TURN	IVOL	AMIHUD	SKEW	KURT	DELAY	X	adj. R^2
coefficient	0.1201	0.0030	-0.0290	-0.0161	0.0285	-0.0033	0.0228	-0.0283	0.1251	-0.0001	-0.0037	-0.0001	0.0008	Yes	0.148
t-stat	*6.47*	*4.27*	*-1.74*	*-2.18*	*7.23*	*-2.61*	*7.35*	*-4.02*	*6.04*	*-0.01*	*-3.99*	*-0.13*	*0.18*		

Panel D: Cross-sectional regressions of earnings momentum on residual information discreteness

	intercept	SUE	residual ID	residual ID ·SUE	PRET	SIZE	BM	TURN	IVOL	AMIHUD	SKEW	KURT	DELAY	X	adj. R^2
coefficient	0.1216	0.0035	-0.0033	-0.0203	0.0278	-0.0033	0.0228	-0.0282	0.1251	-0.0003	-0.0037	-0.0001	0.0007	Yes	0.148
t-stat	*6.54*	*5.00*	*-0.21*	*-2.82*	*7.25*	*-2.59*	*7.29*	*-3.94*	*6.00*	*-0.05*	*-4.10*	*-0.14*	*0.15*		

Table 4: Momentum and Idiosyncratic Volatility

This table reports on the relationship between momentum and idiosyncratic volatility (IVOL). Idiosyncratic volatility is estimated as in Fu (2009) by computing risk-adjusted weekly returns according to the three-factor model over the prior year. IVOL equals the standard deviation of the firm-level residuals from this regression. We sequentially sort stocks into IVOL quintiles, then formation-period return quintiles (PRET) within each of the IVOL quintiles. PRET corresponds to a firm's formation-period return in the prior twelve months after skipping the most recent month. Both unadjusted returns and risk-adjusted returns relative to the three-factor model of Fama and French (1993) are reported. Post-formation momentum returns over a six-month holding period for each of the five IVOL quintiles are presented in Panel A. The momentum profits in Panel B arise from the opposite sequential double-sort which first conditions on PRET, then IVOL to test the marginal influence of IVOL on momentum after controlling for cumulative formation-period returns. The double-sorts in Panel C parallel those in Panel B with IVOL replaced with residual IVOL, which is defined as the residual from the following cross-sectional regression $\text{IVOL}_{i,t} = \gamma_{0,t} + \gamma_{1,t} \left|\text{PRET}\right|_{i,t} + \epsilon_{i,t}^{IVOL}$ to control for the influence of formation-period returns on idiosyncratic volatility. The t-statistics are Newey-West adjusted with six lags and reported in italics.

Panel A: Double-sorts involving idiosyncratic volatility, then formation-period returns

IVOL	Winner 1	2	3	4	Loser 5	Average IVOL	unadjusted six-month return	*t*-stat	three-factor six-month alpha	*t*-stat
high	8.50	7.31	6.16	3.83	-0.40	0.85	8.90	*5.74*	11.28	*8.49*
2	11.60	9.58	8.46	6.78	4.07	0.28	7.53	*5.45*	9.78	*8.92*
3	11.73	10.03	8.93	7.66	5.99	0.13	5.74	*5.67*	7.52	*9.18*
4	10.80	9.24	8.37	7.84	6.36	0.06	4.44	*5.67*	5.59	*8.51*
low	10.06	8.41	7.48	7.14	6.75	0.02	3.31	*5.76*	3.88	*6.50*
high-low						0.83	5.59	*3.95*	7.39	*5.68*

Panel B: Double-sorts involving formation-period returns, then idiosyncratic volatility

IVOL	Winner 1	2	3	4	Loser 5	Average IVOL	unadjusted six-month return	*t*-stat	three-factor six-month alpha	*t*-stat
high	7.11	8.29	8.07	6.54	0.09	0.75	7.02	*4.14*	8.87	*6.80*
2	10.90	9.66	8.92	7.38	3.48	0.29	7.42	*5.30*	9.93	*8.62*
3	11.35	9.80	8.38	7.66	4.93	0.14	6.42	*4.73*	8.92	*8.32*
4	10.95	9.24	8.07	7.45	5.94	0.08	5.01	*4.13*	7.08	*6.90*
low	10.33	8.72	7.78	7.07	5.99	0.03	4.34	*4.26*	6.13	*7.28*
high-low						0.72	2.68	*2.07*	2.75	*2.44*

Panel C: Double-sorts involving formation-period returns, then residual idiosyncratic volatility

residual IVOL	Winner 1	2	3	4	Loser 5	Average residual IVOL	unadjusted six-month return	*t*-stat	three-factor six-month alpha	*t*-stat
high	7.31	8.3	8.01	6.5	0.44	0.31	6.87	*4.17*	9.60	*6.42*
2	9.62	9.42	8.74	7.47	3.86	-0.19	5.76	*5.77*	7.97	*7.33*
3	10.83	9.6	8.39	7.56	5.08	-0.33	5.75	*4.64*	8.25	*8.09*
4	10.68	9.19	7.98	7.46	5.58	-0.40	5.10	*4.61*	7.05	*7.51*
low	12.37	9.22	8.06	7.11	5.75	-0.49	6.62	*4.78*	8.36	*8.37*
high-low						0.80	0.25	*0.37*	1.24	*1.04*

Table 5: Analyst Forecasts and Information Discreteness

This table reports on the relationship between earnings surprises, defined relative to the consensus forecast of analysts, and information discreteness. Information discreteness (ID) is defined in equation (1) as sgn(PRET) $\cdot$ [$\%neg - \%pos$] where $\%pos$ and $\%neg$ denote the respective percentage of positive and negative daily returns during the formation period. PRET corresponds to a firm's formation-period return in the prior twelve months after skipping the most recent month. Information discreteness captures the distribution of daily returns across this formation period. Continuous information arrives frequently in small amounts while discrete information arrives infrequently in large amounts. Low values of ID are generated by continuous information while high values of ID are generated by discrete information. The relationship between analyst forecast errors (SURP) and information discreteness is examined by the following regression, $|\mathrm{SURP}|_{i,t} = \beta_0 + \beta_1\,\mathrm{ID}_{i,t} + \beta_2\,\mathrm{PRET}_{i,t} + \beta_3\,\mathrm{DISP}_{i,t} + \beta_4\,\mathrm{COVER}_{i,t} + \beta_5\,\mathrm{BM}_{i,t} + \beta_6\,\mathrm{SIZE}_{i,t} + \beta_7\,\mathrm{TURN}_{i,t} + \beta_8\,\mathrm{IO}_{i,t} + \epsilon_{i,t}$. The independent variables, besides information discreteness and formation-period returns (PRET), are analyst forecast dispersion (DISP), analyst coverage (COVER), book-to-market ratios (BM), size (SIZE), turnover (TURN), and institutional ownership (IO). Panel A reports on their respective β coefficients while the results in Panel B replace information discreteness defined by signed daily returns with an alternative measure of information discreteness denoted ID_f in equation (10) as sgn(CUMREV) $\cdot$ [$\%downward - \%upward$] based on signed analyst forecast revisions. The cumulative revision during the formation period is denoted CUMREV, and its sign is +1 when CUMREV > 0 and -1 when CUMREV < 0. For every firm-fiscal year, we define CUMREV as the difference between the last consensus forecast before an annual earnings announcement and the first forecast. The results in Panel C and Panel D also involve this alternative measure for information discreteness. Panel C reports on the relationship between price momentum and ID_f using the following Fama-MacBeth regression $r_{i,t+h} = \beta_0 + \beta_1\,\mathrm{PRET}_{i,t} + \beta_2\,\mathrm{ID}_{f\,i,t} + \beta_3\,(\mathrm{ID}_f \cdot \mathrm{PRET})_{i,t} + \beta_4\,\mathrm{SUE}_{i,t} + \beta_5\,\mathrm{SIZE}_{i,t} + \beta_6\,\mathrm{BM}_{i,t} + \beta_7\,\mathrm{TURN}_{i,t} + \beta_8\,\mathrm{IVOL}_{i,t} + \beta_9\,\mathrm{AMIHUD}_{i,t} + \beta_{10}\,\mathrm{SKEW}_{i,t} + \beta_{11}\,\mathrm{KURT}_{i,t} + \beta_{12}\,\mathrm{DELAY}_{i,t} + \alpha\,X_{i,t} + \epsilon_{i,t+h}$ while Panel D reports on the relationship between earnings momentum and ID_f using the following Fama-MacBeth regression $r_{i,t+h} = \beta_0 + \beta_1\,\mathrm{SUE}_{i,t} + \beta_2\,\mathrm{ID}_{f\,i,t} + \beta_3\,(\mathrm{ID}_f \cdot \mathrm{SUE})_{i,t} + \beta_4\,\mathrm{PRET}_{i,t} + \beta_5\,\mathrm{SIZE}_{i,t} + \beta_6\,\mathrm{BM}_{i,t} + \beta_7\,\mathrm{TURN}_{i,t} + \beta_8\,\mathrm{IVOL}_{i,t} + \beta_9\,\mathrm{AMIHUD}_{i,t} + \beta_{10}\,\mathrm{SKEW}_{i,t} + \beta_{11}\,\mathrm{KURT}_{i,t} + \beta_{12}\,\mathrm{DELAY}_{i,t} + \alpha\,X_{i,t} + \epsilon_{i,t+h}$. The additional independent variables in this regression include idiosyncratic volatility (IVOL), Amihud's illiquidity measure (AMIHUD), skewness (SKEW), kurtosis (KURT), and the price delay measure (DELAY) in equation (4). The X vector contains additional control variables: earnings-to-price ratios, total assets, capital expenditures to total assets, sales growth, institutional ownership, and analyst coverage. The t-statistics are Newey-West adjusted with six lags and reported in italics.

Panel A: Cross-sectional regressions of analyst forecast errors on information discreteness defined by returns

	intercept	ID	PRET	DISP	COVER	BM	SIZE	TURN	IO	adj. R^2
coefficient	0.0306	-0.0282	-0.0060	-0.0039	-0.0008	-0.0250	-0.0011	0.0042	-0.0023	0.186
t-stat	*6.39*	*-4.66*	*-6.66*	*-3.41*	*-2.17*	*-4.68*	*-5.82*	*4.13*	*-3.17*	

Panel B: Cross-sectional regressions of analyst forecast errors on information discreteness defined by analyst forecasts

	intercept	ID_f	PRET	DISP	COVER	BM	SIZE	TURN	IO	adj. R^2
coefficient	0.0013	-0.0018	-0.0015	0.0005	-0.0002	0.0050	-0.0001	0.0009	-0.0003	0.194
t-stat	*1.64*	*-3.34*	*-7.47*	*1.12*	*-1.50*	*14.86*	*-2.59*	*2.84*	*-1.83*	

Panel C: Cross-sectional regressions of price momentum on information discreteness defined by analyst forecasts

	intercept	PRET	ID_f	$ID_f \cdot$PRET	SUE	SIZE	BM	TURN	IVOL	AMIHUD	SKEW	KURT	DELAY	X	adj. R^2
coefficient	0.1232	0.0434	0.1107	-0.2355	0.0022	-0.0034	0.0208	-0.0033	-0.0253	0.0900	-0.0054	-0.0004	0.0020	Yes	0.126
t-stat	*5.90*	*8.51*	*6.40*	*-4.50*	*2.97*	*-2.39*	*4.18*	*-0.39*	*-1.95*	*1.19*	*-3.71*	*-2.66*	*0.36*		

Panel D: Cross-sectional regressions of earnings momentum on information discreteness defined by analyst forecasts

	intercept	SUE	ID_f	$ID_f \cdot$ SUE	PRET	SIZE	BM	TURN	IVOL	AMIHUD	SKEW	KURT	DELAY	X	adj. R^2
coefficient	0.1236	0.0019	0.0622	-0.0496	0.0398	-0.0034	0.0207	-0.0029	-0.0226	0.1064	-0.0056	-0.0004	0.0013	Yes	0.123
t-stat	*5.89*	*2.38*	*4.39*	*-6.68*	*8.48*	*-2.40*	*4.14*	*-0.34*	*-1.73*	*1.38*	*-3.88*	*-2.48*	*0.23*		

Table 6: Origin of Information Discreteness

This table addresses the economic determinants of information discreteness (ID), which is defined in equation (1) as sgn(PRET) $\cdot$ [$\%neg - \%pos$] where $\%pos$ and $\%neg$ denote the respective percentage of positive and negative daily returns during the formation period. PRET corresponds to a firm's formation-period return in the prior twelve months after skipping the most recent month. Information discreteness captures the distribution of daily returns across this formation period. Continuous information, which corresponds to low ID, arrives frequently in small amounts while discrete information, which corresponds to high ID, arrives infrequently in large amounts. The results below are from the Fama-MacBeth regression in equation (13), $\text{ID}_{i,t} = \beta_0 + \beta_1 \,\text{PR}_{i,t} + \beta_2 \,\text{MEDIA}_{i,t} + \beta_3 \,\text{COVER}_{i,t} + \beta_4 \,\text{SIZE}_{i,t} + \beta_5 \,\text{IO}_{i,t} + \beta_6 \,|\text{PRET}|_{i,t} + \epsilon_{i,t}$ whose independent variables are press releases by management that are not covered by the media within seven days (PR), news articles in the media (MEDIA) that are not attributable to press releases within the prior seven days, analyst coverage (COVER), firm size (SIZE), institutional ownership (IO), and the absolute value of formation-period returns (|PRET|). PR and MEDIA refer to the number of press releases without media coverage and the number of news articles that are not attributable to press releases in the prior year, respectively. This regression is conducted separately for stocks whose formation-period returns are above and below the cross-sectional median since ID is an interaction variable whose interpretation is conditional on formation-period returns. The correlations between the independent variables are recorded in Panel A. Panel B reports the coefficients of the cross-sectional regression for winner stocks whose formation-period returns are above the median, which have been multiplied by 100 for ease of interpretation, and Panel C reports these coefficients for loser stocks whose formation-period returns are below the media. The t-statistics are Newey-West adjusted with six lags and reported in italics.

Panel A: Correlations between independent variables

	ID	PR	MEDIA	COVER	SIZE	IO	|PRET|
ID	1						
PR	0.014	1					
MEDIA	-0.020	-0.134	1				
COVER	0.011	0.139	0.297	1			
SIZE	0.012	0.185	0.332	0.648	1		
IO	0.043	0.162	0.180	0.425	0.535	1	
|PRET|	-0.149	0.005	0.001	-0.073	0.011	-0.066	1

Panel B: Information discreteness and firm characteristics for firms with above-median PRET

	intercept	PR	MEDIA	COVER	SIZE	IO	|PRET|	adj. R^2
coefficient	0.0892	-0.0015	0.0048	-0.0030	-0.0078	-0.0049	-0.0273	0.383
t-stat	*16.45*	*-4.40*	*9.63*	*-2.62*	*-18.67*	*-4.38*	*-19.17*	

Panel C: Information discreteness and firm characteristics for firms with below-median PRET

	intercept	PR	MEDIA	COVER	SIZE	IO	|PRET|	adj. R^2
coefficient	-0.0624	0.0003	0.0008	-0.0029	0.0042	0.0006	-0.1399	0.454
t-stat	*-12.35*	*0.96*	*1.68*	*-3.00*	*12.30*	*0.54*	*-104.34*	

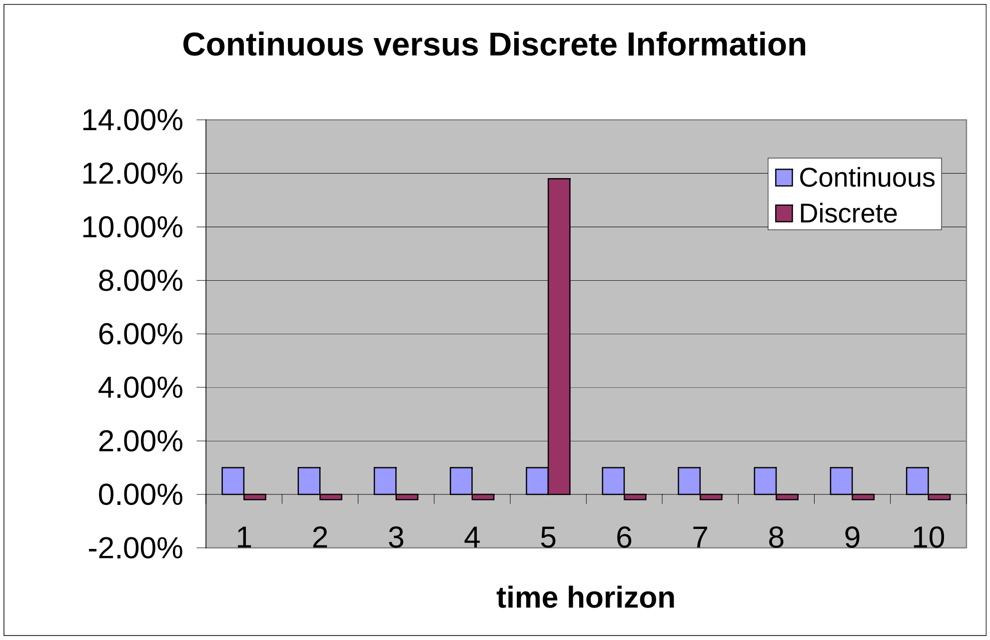

Figure 1 This figure provides a visual illustration of the difference between continuous information versus discrete information over a ten-period horizon. Information discreteness (ID) is defined in equation (1) to capture the distribution of daily returns across the formation period. Continuous information arrives frequently in small amounts while discrete information arrives infrequently in large amounts. Observe that the cumulative amount of information during this horizon is identical, at 10%, where the magnitude of information is represented by its cumulative return implications. According to its definition in equation (1), the continuous information has an ID measure of -1 (its minimum) while the discrete information has an ID measure of 0.8 (approaching its maximum).

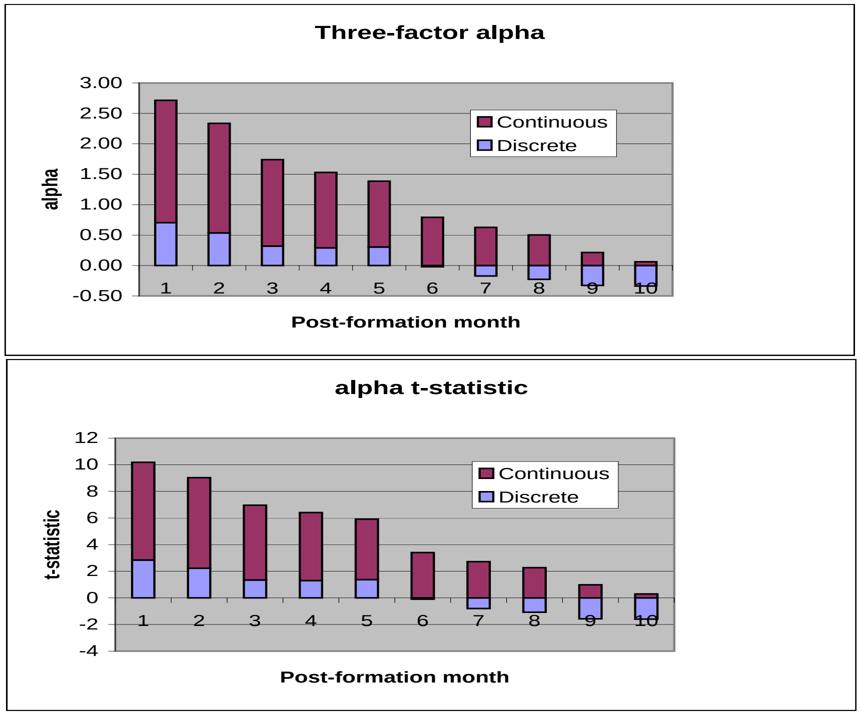

Figure 2 This figure plots risk-adjusted momentum profits in the continuous and discrete information portfolios from one to ten months after portfolio formation. Information discreteness is defined in equation (1) to capture the distribution of daily returns across the formation period. Continuous information arrives frequently in small amounts while discrete information arrives infrequently in large amounts. Momentum profits in month $t+x$, where x ranges from 1 to 10, based on double-sorted portfolios formed in month t according to formation-period returns and information discreteness. These momentum profits are not cumulative. Instead, they are time series averages of holding-period returns in a single month after portfolio formation, with the month of portfolio formation varying across the sample period.